THE USE OF MACHINE LEARNING IN PAEDIATRIC NUTRITION

Aneurin Young[a,b] (ORCID: 0000-0003-3549-3813, Twitter: @AneurinYoung), Mark J Johnson[a,c] (0000-0003-1829-9912, @MarkJohnson800), R Mark Beattie[a] (0000-0003-4721-0577, @RMBeattie50).

[a]Southampton Children's Hospital, University Hospital Southampton NHS Foundation Trust, UK; [b]University of Southampton, UK; [c]NIHR Southampton Biomedical Research Centre, University Hospital Southampton NHS Foundation Trust and University of Southampton, UK.

Corresponding Author: Prof R Mark Beattie, Children's Hospital, University Hospital Southampton NHS Foundation Trust, Tremona Road, Southampton, SO16 6YD, UK [mark.beattie@uhs.nhs.uk] 02380777222

Word Count: 2727

Abstract

Purpose of Review

In recent years, there has been a burgeoning interest in using machine learning methods. This has been accompanied by an expansion in the availability and ease of use of machine learning tools and an increase in the number of large, complex datasets which are suited to machine learning approaches. This review summarises recent work in the field and sets expectations for its impact in the future.

Recent Findings

Much work has focused on establishing good practices and ethical frameworks to guide the use of machine learning in research. Machine learning has an established role in identifying features in "omics" research and is emerging as a tool to generate predictive models to identify people at risk of disease and patients at risk of complications. They have been used to identify risks for malnutrition and obesity. Machine learning techniques have also been used to develop smartphone apps to track behaviour and provide healthcare advice.

Summary

Machine learning techniques are reaching maturity and their impact on observational data analysis and behaviour change will come to fruition in the next five years. A set of standards and best practices are emerging and should be implemented by researchers and publishers.

Key words: Machine learning, artificial intelligence, modelling, nutrition, child health.

Introduction

Clinicians and scientists alike are increasingly exposed to vast amounts of data. As the availability of genomic, metabolomic and microbiomic data expands, fuelled by a progressive increase in their affordability, life scientists have become experts in managing the vast and complex datasets these techniques generate. In the ward and in the neonatal nursery, comprehensive **clinical information systems** record a continuous stream of data about our patients. In the community, the ubiquity of smartphones offers unrivalled potential for understanding the lives and choices of those buying and consuming food. Each of these environments and data sources represents an opportunity to understand how nutrition impacts the lives of people in our communities and the health of the children for whom we care when they are unwell. However, this opportunity brings a raft of challenges and risks.

This review aims to set out recent discoveries in the key areas of machine learning applied to paediatric nutrition. They are as diverse as the field of nutrition itself, ranging from investigations of eating behaviour at population level to insights into the molecular mechanisms of nutritional health and disease. Table 1 defines some of the key terms and techniques discussed in this review, with these terms highlighted in bold in the text.

Table 1. Definitions of machine learning terms and techniques used in this paper.

Term	Definition
Artificial neural network	A machine learning approach inspired by networks in the brain. A neural network includes an input layer, an output layer and a number of hidden layers where nodes (or "neurons") process information and pass it to the next layer. The outcome layer returns a prediction based on the input values.
Artificial intelligence (AI)	A model capable of performing complex tasks. Whilst AI formally encompasses machine learning, the terms are often used interchangeably.
Chatbot	An interface which aims to provide information to the user in a manner similar to a human conversation, often using natural language processing.
Clinical information system (CIS)	Any computer system designed to gather, organise and store clinical data on patients. CISs can range from simple tables to extremely complex datasets gathering many channels of minute-to-minute data about patients. They are a rich data source for machine learning approaches.

Decision tree	A hierarchical model in which sequential analysis of conditions results in a prediction, which each sub-analysis described as a node. They are often combined to form random forests.
Elastic net regularization	An approach to linear regression which aims to select features and deal with collinearity and correlation amongst candidate variables. It uses elements of Lasso and Ridge regression to form effective and parsimonious models.
Explainable (or interpretable) AI	A group of tools which aim to explain how machine learning models make their predictions. They are broadly designed to address the "black box" problem in AI, whereby models make predictions based on analysis which is hidden from the end-user (and the designer of the model). They may help to improve the transparency of ML models.
Extreme gradient boosting (XGBoost)	Gradient boosting is an ML approach in which small weak models are used to refine and improve a stronger model. Extreme gradient boosting is a specific implementation of this approach which also includes decision trees.
Generative adversarial networks	An ML technique in which one model aims to generate plausible new examples of the input data. A second model aims to identify whether the examples are real or generated and its decisions are used to refine the model.
Hybrid ensemble methods	A method to combine the predictions from multiple ML models to make predictions which are more reliable than any individual approach.
K-nearest neighbours	A classification technique which uses input variables to plot observations in multidimensional space and identify groups and classes of similar cases.
Least absolute shrinkage and selection operator (LASSO)	A technique to simplify and improve regression models (especially linear and logistic regression models) which selects the most important features (variables).
Machine learning (ML)	A model which can be trained on training data to make predictions or analyse new data. ML is formally a subset of artificial intelligence, but the terms are often used interchangeably.
Natural language processing	Any of a group of related algorithms which aim to understand natural human language and/or to provide responses to the user which mimic human conversation.
Principal component analysis (PCA)	A statistical approach to reduce the dimensionality of complex high-dimensional data, summarising the variability of the data into a number of components which are independent of (orthogonal to) each other.
Random forest	A model formed by combining the predictions of an ensemble of a large number of decision trees.
Ridge regression	An approach to linear or logistic regression which deals with collinearity amongst input variables to form more reliable and generalisable predictions.
Shapley additive explanations (SHAP)	An explainable AI approach which uses elements of game theory to determine the importance and effect size of input variables in an ML model on the prediction made by that model.

Opportunities and Risks in Machine Learning for Paediatric Nutrition

The first challenge is to understand how this morass of data can be processed to discover meaning and improve care. Machine learning (ML) and artificial intelligence (AI) are powerful tools to interpret complex data. Ashton and co-workers summarised the available models and their potential to influence the long-term clinical care of children.[1**] They emphasised the importance of clinically informed a priori identification of candidate variables, data curation and model validation to assure the reliability and relevance of findings arising from machine learning models.

The ethical implications of such widespread data collection should also be considered. Thomas and co-workers offer a lucid and practical guide to implementing machine learning approaches.[2**] Their work focuses on gaining important insights whilst avoiding the ethical pitfalls of previous attempts to analyse big data. They emphasise the importance of publishers and reviewers in the process of ensuring good practice in statistical modelling, including a checklist for ethical and effective application of machine learning in nutritional research. Data literacy has failed to keep pace with the expansion of the machine learning approaches available to nutrition researchers. Guides to good statistical practices are needed to ensure that the insights from machine learning are robust and equitably applied. Transparency will be aided by the burgeoning interest in **explainable AI**, a group of methods used to provide insights into how machine learning models reach conclusions or make predictions.

The Genome, Metabolome and Microbiome

Over the last year, several groups have used machine learning approaches to investigate associations between disease states and the intestinal microbiome. Park and Kang pooled stool microbial information from five studies in developed and developing countries to investigate associations with short stature in children.[3] They employed several machine learning approaches to identify differences. Firstly, enterobacteria were clustered using **principal component analysis (PCA)**. Predictive models for short stature based on fecal microbiota were then formed using **extreme gradient boosting (XGBoost)** with explanations provided by **Shapley additive explanations (SHAP)**. This **explainable AI** approach allowed the identification of stool microbiome features associated with short stature. Robertson and co-workers also examined stunting, focusing on a group of children in Zimbabwe who had been enrolled in a randomized trial of improved sanitation and feeding practices.[4*] They also used XGBoost and found weak associations between growth and taxonomic classifications of the microbiome, but significant associations between growth and the functional metagenome. A Mexican group were especially interested in how dietary intake of animal fats related to gut microbiota and brain connectivity.[5*] They used machine learning approaches (including r**andom forests**) and network theory to determine differences between brain and microbiota networks depending on dietary intakes.

Midya and co-workers used a novel method based on random forests to identify groups of bacteria ("cliques" as they were described in the study) which were associated with prenatal lead exposure in pre-pubertal children.[6*] As with much of the current research into the microbiome, the study focused on developing methods to understand complex interactions between different bacteria. Similarly, a Spanish collaboration used genomic and biochemical predictors of insulin resistance in adolescents to act as a case study.[7*] Their paper highlighted the importance of careful model selection and data preparation to ensure that reliable and clinically important results were obtained. Interestingly, they caution against hasty integration of different data in a multi-omics approach, choosing first to model each data type individually.

Two recent studies used **random forest** approaches to identify the most important features in metabolomic predictions of disease states. In California, a group examined relationships between breastmilk composition and risk of neurodevelopmental delay, using random forests to identify the most important features in their models.[8] Another American group used random forests to identify which clinical and stool metabolome features are most predictive of parenteral-nutrition associated cholestasis in preterm infants.[9*] They identified stool sphingolipids as a potential biomarker of impending cholestatic disease.

The studies in this section highlight the emerging importance of machine learning approaches to "omics" data. Whilst certain techniques now have a strong track record (for example feature reduction using **random forests**), other applications are not yet fully established. Many of these investigations seek new methods to assess relationships and there are frequent reminders of the importance of model selection, data preparation and proper validation. As standards are set to ensure good practice, investigations into the omics of nutrition will gain in robustness, applicability and trustworthiness.

Population-Level Studies of Disease Risk

With its ability to handle large volumes of complex data and its tolerance for confounding and collinearity, machine learning is proving a useful tool in the examination of nutrition and diet at scale in populations.

Malnutrition

During recent years, several groups have sought to use these approaches to screen or monitor for malnutrition in developing countries. In Papua New Guinea, researchers used **XGBoost** augmented with **SHAP** to understand the children and communities most at risk for stunting, aiding efforts to focus nutritional interventions to those most in need.[10*] Khan and Yunus examined risk factors for malnutrition in children in five countries in sub-Saharan Africa.[11*] They found that a **hybrid ensemble method** integrating **random forests**, **XGboost**, **decision trees** and **k-nearest neighbours** outperformed any single ML approach in isolation. A South African group provided expert assessments of weight-for-age growth curves to an **artificial neural network** which was then trained to recognise signs of impending severe acute malnutrition.[12*] The artificial neural network outperformed simpler prediction methods.

Obesity and Eating Disorders

Artificial neural networks were also employed by an international collaboration to predict overweight and obesity in children, identifying gestational age, daily caloric intake and birthweight as key indicators of risk.[13*] A Canadian group used features extracted from growth trajectories to predict whether a child would become overweight or obese.[14] They used **random forests** and **XGBoost**, with some explainability provided by analysing the random forest decision trees.

A case control study used retrospective sociocultural and psychological features in early childhood to predict later onset of eating disorders.[15**] They used novel prediction rule ensembles to identify interacting features whose clusters may be associated with the outcome of interest. They also used **LASSO** to generate more parsimonious logistic regression models. The use of these techniques did not provide a significant accuracy benefit compared to conventional logistic regression. Each of these studies highlight the use of ML models to build more reliable predictors of disease. It is important to note that they do not always perform more strongly than simpler logistic regression models, although they may produce equally accurate models with fewer variables, improving their ease of application for screening applications.

Tracking Food Consumption and Behaviour

Two recent studies have used body-worn cameras to track food consumption patterns in children. The first developed algorithms to automatically detect and classify food images from body worn camera footage.[16*] The second study used mobile phone photos taken by participants to classify foodstuffs and estimate nutrient intakes.[17*] The same system was validated in Vietnam.[18*] Another group focused on food labels, demonstrating that **natural language processing** models could accurately determine nutrient contents of food from images of their packaging.[19] Whilst still in their infancy, these approaches to food intake monitoring show promise in allowing large-scale data gathering using modern technology to reduce the time and costs associated with traditional food intake interviews. These approaches were reviewed by Neves and co-workers.[20*]

Other groups have focused on assessing the classroom and social media environments as they relate to food and diet. A Spanish study used k-means clustering to identify groups within classrooms, identifying key behaviours within those groups which influenced eating patterns and risk of obesity.[21] Taking a wider view, a group in Texas used **natural language processing** to assess attitudes to breastfeeding based on Twitter posts.[22] Quantitative methods for assessing behaviour and social dynamics are likely to use ML models to strengthen insights into how communities form and influence dietary patterns in multiple contexts.

Tools and Apps

As smartphones have been adopted across the world, apps to manage dietary interventions have been posited as an approach to several diseases. Over the last two years, several groups have developed and assessed smartphone apps targeting the dietary behaviour of different groups.

Healthcare Advice

A group in America recognised a lack of healthcare information available to parents during their child's infancy.[23*] Unequal access to healthcare information deepened racial disparities. The researchers set out to create an app to provide advice to parents of infants. A **chatbot** was developed, using **natural language processing** machine learning techniques, to receive queries from parents and return appropriate advice. Such natural language processing capabilities allow large-scale provision of dietary advice and are likely to be especially useful to communities who are under-served by current healthcare systems.

Adolescent Behaviour

Chatbots have also been explored as a means to influence adolescent dietary behaviour in recent years. A review in 2023 summarised progress with chatbots in this field.[24*] The review identified five papers in the scientific literature which focused on the use of chatbots to influence adolescent diets and physical activity. They were particularly interested the acceptability of these techniques to their target audience. The apps were structured around a **natural language processing** algorithm. These studies mostly involved small numbers of adolescents. A local youth panel in Australia were concerned about the use of such apps for profit or that they might provide inaccurate information or replace established sources of healthcare advice.[24*] This project illustrated the nascent state of many of these efforts and reflected the ethical concerns of a generation who have grown up in the information age. Today's adolescents have high expectations for their interactions with apps, as highlighted by a group of Vietnamese girls who consulted on the design of an app to track and improve food choices.[25*] They expected the app to provide highly personalised advice taking their height, weight and medical issues into consideration when giving feedback. This acts as a challenge to software developers and scientists to understand how personal circumstances should influence dietary advice.

Dietary Planning

Artificial intelligence has also contributed to a programme offering nutritional advice to obese adolescents and their parents.[26] This scheme integrated information from activity monitors with a mobile game and AI-informed personalised dietary advice for each parent-child dyad. They confirmed a change in some metabolic factors during the intervention (including glycated haemoglobin) alongside changes in diet-related behaviour. Delving deeper in the field of diet planning, a Korean group used **generative adversarial networks** and reinforcement learning to generate novel diet plans for children attending daycare facilities.[27] In Brazil, a large study is being planned to analyse the growth of millions of children to identify growth patterns and use machine learning to predict obesity.[28*] . A Saudi group has focused on guiding the vital dietary management of maple syrup urine disease.[29, 30*] An app was made available to implement a set of rules to guide the nutritional care of infants. A more complex app was developed using AI-based image recognition to assess the children's and to offer dietary recommendations to manage their disease. The impact of this app on disease control is yet to be analysed.

Whether it is by influencing the behaviour of a whole population of adolescents or micro-managing the diet of a child with a severe inborn error of metabolism, AI approaches and ML models look likely to contribute to mobile apps which improve nutrition. To date, many of these projects have been pilots or small-scale rollouts. Their impacts remain uncertain until large-scale implementation can be demonstrated.

Nutrition and Growth in Sick Infants

Three recent studies have built models to predict outcomes for infants requiring medical care. A Turkish group aimed to identify infants at risk of poor weight gain during neonatal hospitalisation.[31*] It aimed to augment an established nutrition screening tool and assessed multiple machine learning approaches, finding that a regression task (predicting weight at discharge) was best handled by an **elastic net** model and classification to predict whether any weight would be gained was best handled by **random forests**. **SHAP** was used to identify the most salient features for each selected model and to improve prediction accuracy (in this specific single-centre cohort). Elastic net regression was also used to identify the most important factors associated with ongoing breastfeeding for infants with single ventricle congenital heart disease.

A secondary analysis of a randomised controlled trial used **random forests** to assess whether using a mixed lipid emulsion including fish oil improved neurodevelopmental outcomes in preterm infants exposed to parenteral nutrition.[32*] It did not.

Each of these studies used datasets with complex, interacting and diverse candidate variables for inclusion in prediction models. Whereas traditional linear or logistic regression approaches can struggle to interpret these data in clinically meaningful ways, machine learning approaches such as **elastic net regression** and **random forests** can achieve powerful predictions with more parsimonious models. In this way, they help to identify the most important predictive factors and reduce the complexity of the data collection required to make clinical predictions and stratifications.

Conclusion

Machine learning models have found their place within many elements of research into children's nutrition. They have become vital tools to process the wealth of data arising from genomic, metabolomic and microbiome research, finding patterns within these complex data which help to illuminate their roles in growth and nutrition. At the population level, ML approaches have helped to build stronger, simpler and more accurate screening tools for important outcomes. Where resources are limited or demand is high, the rapid expansion in the availability of machine learning tools will help to focus available resources where they are most needed, especially as access to high-power computing becomes cheaper and more accessible They are especially well suited to large datasets with complex and varied data types. Machine learning also promises to help clinicians caring for hospitalised infants to identify those most at risk of complications, spurring professionals to ameliorate threats to their recovery. **Natural language processing** and image processing techniques have been combined to build apps to track nutritional intake and generate dietary advice which is presented in an accessible way to young people via smartphone apps. Implementing these technologies at scale may provide opportunities to address the obesity epidemic which is spreading from the developed world into areas undergoing rapid economic and cultural change.

Across this spectrum, a handful of themes emerge:

- Source data for machine learning models must be cleaned, validated and checked for fidelity to ensure the reliability of the resulting analysis.
- Selection of appropriate ML approaches is vital. The chosen techniques must be appropriate to the dataset and the research question, and they must provide real, clinically meaningful advantages over traditional methods.
- Models must be robust and contain proper validation and testing to ensure that they are generalisable to the population in question and do not perpetuate biases or discrimination in the source data.
- Data literacy must be elevated so that those building, evaluating and using ML models can do so appropriately and reliably. This is particularly relevant in the sphere of academic publishing, where guidelines and standards are currently being negotiated.

By heeding these best practices, the promise of machine learning can be realised to guide the nutritional care of sick children and the population interventions required to improve the health of the next generation.

KEY POINTS

- Machine learning techniques have become increasingly widely used in nutritional research, especially in metabolomics, the microbiome, disease risk prediction and apps to influence dietary choices and behaviour.
- Reliable outcomes from machine learning approaches require careful data curation, method selection and model validation.
- A framework of standards and guidelines is emerging to ensure that researchers and publishers use machine learning in a way which is validated, ethical, free from bias and transparent.

ACKNOWLEDGEMENTS

None

FINANCIAL SUPPORT AND SPONSORSHIP

Aneurin Young is in a Clinical Lecturer post at the University of Southampton funded by the NIHR.

CONFLICTS OF INTEREST

None

References

** 1. Ashton JJ, Young A, Johnson MJ, Beattie RM. Using machine learning to impact on long-term clinical care: principles, challenges, and practicalities. Pediatr Res. 2023;93(2):324-33. ***A useful primer on machine learning techniques in paediatric research, alongside a visual guide to some common machine learning techniques.***

** 2. Thomas DM, Kleinberg S, Brown AW, Crow M, Bastian ND, Reisweber N, et al. Machine learning modeling practices to support the principles of AI and ethics in nutrition research. Nutr Diabetes. 2022;12(1):48. ***This important paper lays out comprehensive and pragmatic guidance for using machine learning. It advises the researcher and sets out clear and exacting standards for publishers assessing and presenting work using machine learning.***

3. Park S, Kang S. Association of pooled fecal microbiota on height growth in children According to enterotypes. J Pediatr Gastroenterol Nutr. 2023

* 4. Robertson RC, Edens TJ, Carr L, Mutasa K, Gough EK, Evans C, et al. The gut microbiome and early-life growth in a population with high prevalence of stunting. Nat Commun. 2023;14(1):654. ***Highlights the potential for machine learning to influence research into stunting in developing countries.***

* 5. Ramírez-Carrillo E, I GS, López-Corona O, Rojas-Ramos OA, Falcón LI, Gaona O, et al. Similar connectivity of gut microbiota and brain activity networks is mediated by animal protein and lipid intake in children from a Mexican indigenous population. PLoS One. 2023;18(6):e0281385. ***Complex and novel combination of machine learning and network methods.***

* 6. Midya V, Lane JM, Gennings C, Torres-Olascoaga LA, Gregory JK, Wright RO, et al. Prenatal Lead Exposure Is Associated with Reduced Abundance of Beneficial Gut Microbial Cliques in Late Childhood: An Investigation Using Microbial Co-Occurrence Analysis (MiCA). Environ Sci Technol. 2023;57(44):16800-10. ***A novel machine learning approach to identifying clusters of interacting bacteria.***

* 7. Torres-Martos Á, Bustos-Aibar M, Ramírez-Mena A, Cámara-Sánchez S, Anguita-Ruiz A, Alcalá R, et al. Omics Data Preprocessing for Machine Learning: A Case Study in Childhood Obesity. Genes (Basel). 2023;14(2) ***This report uses a case study to illustrate key elements of effective use and presentation of machine learning models. It will be instructive to any team setting out to perform machine learning analysis.***

8. Li K, Bertrand K, Naviaux JC, Monk JM, Wells A, Wang L, et al. Metabolomic and exposomic biomarkers of risk of future neurodevelopmental delay in human milk. Pediatr Res. 2023;93(6):1710-20.

* 9. Moutinho TJ, Powers DA, Hanson GF, Levy S, Baveja R, Hefner I, et al. Fecal sphingolipids predict parenteral nutrition-associated cholestasis in the neonatal intensive care unit. JPEN J Parenter Enteral Nutr. 2022;46(8):1903-13. ***This paper highlights the potential of machine learning to identify key risk factors from complex datasets.***

* 10. Shen H, Zhao H, Jiang Y. Machine Learning Algorithms for Predicting Stunting among Under-Five Children in Papua New Guinea. Children (Basel). 2023;10(10) ***Further evidence of the importance of feature selection in determining risk of stunting. An example of the use of explainable AI.***

* 11. Khan MNA, Yunus RM. A hybrid ensemble approach to accelerate the classification accuracy for predicting malnutrition among under-five children in sub-Saharan African countries. Nutrition. 2023;108:111947. ***A worked example of using complex ensemble methods to build models with strong predictive capabities.***

* 12. Nel S, Feucht UD, Nel AL, Becker PJ, Wenhold FAM. A novel screening tool to predict severe acute malnutrition through automated monitoring of weight-for-age growth curves. Matern Child Nutr. 2022;18(3):e13364. ***A novel approach to growth trajectory analysis which may be applicable to other population groups.***

* 13. Nobre IG, Jurema Santos GC, Santos de Almeida Oliveira TLP, Ribeiro IDC, Dos Santos RM, Rodrigues CPS, et al. Food consumption habits, gestational age and birth weight are predictive for children with excess weight: An analysis based on artificial neural network. Nutr Health. 2022:2601060221124040. ***Promising results in identifying those at risk of obesity.***

14. Massara P, Lopez-Dominguez L, Bourdon C, Bassani DG, Keown-Stoneman CDG, Birken CS, et al. A novel systematic pipeline for increased predictability and explainability of growth patterns in children using trajectory features. Int J Med Inform. 2023;177:105143.

** 15. Krug I, Linardon J, Greenwood C, Youssef G, Treasure J, Fernandez-Aranda F, et al. A proof-of-concept study applying machine learning methods to putative risk factors for eating disorders: results from the multi-centre European project on healthy eating. Psychol Med. 2023;53(7):2913-22. ***An interesting example of the application of machine learning, highlighting the strengths and weaknesses of traditional logistic regression and novel machine learning approaches when applied to a specific dataset.***

* 16. Elbassuoni S, Ghattas H, El Ati J, Zoughby Y, Semaan A, Akl C, et al. Capturing children food exposure using wearable cameras and deep learning. PLOS Digit Health. 2023;2(3):e0000211. ***A useful example of image identification.***

* 17. Folson GK, Bannerman B, Atadze V, Ador G, Kolt B, McCloskey P, et al. Validation of Mobile Artificial Intelligence Technology-Assisted Dietary Assessment Tool Against Weighed Records and 24-Hour Recall in Adolescent Females in Ghana. J Nutr. 2023;153(8):2328-38. ***A further example of adapting food recognition approaches to diverse populations.***

* 18. Nguyen PH, Tran LM, Hoang NT, Trương DTT, Tran THT, Huynh PN, et al. Relative validity of a mobile AI-technology-assisted dietary assessment in adolescent females in Vietnam. Am J Clin Nutr. 2022;116(4):992-1001. ***An interesting comparison of new and more established methods of diet assessment.***

19. Hu G, Ahmed M, L'Abbé MR. Natural language processing and machine learning approaches for food categorization and nutrition quality prediction compared with traditional methods. Am J Clin Nutr. 2023;117(3):553-63.

***** 20. Neves PA, Simões J, Costa R, Pimenta L, Gonçalves NJ, Albuquerque C, et al. Thought on Food: A Systematic Review of Current Approaches and Challenges for Food Intake Detection. Sensors (Basel). 2022;22(17) ***A helpful overview of food intake detection using machine learning.***

21. Marqués-Sánchez P, Martínez-Fernández MC, Benítez-Andrades JA, Quiroga-Sánchez E, García-Ordás MT, Arias-Ramos N. Adolescent relational behaviour and the obesity pandemic: A descriptive study applying social network analysis and machine learning techniques. PLoS One. 2023;18(8):e0289553.

22. Jagarapu J, Diaz MI, Lehmann CU, Medford RJ. Twitter discussions on breastfeeding during the COVID-19 pandemic. Int Breastfeed J. 2023;18(1):56.

***** 23. Mane HY, Channell Doig A, Marin Gutierrez FX, Jasczynski M, Yue X, Srikanth NP, et al. Practical Guidance for the Development of Rosie, a Health Education Question-and-Answer Chatbot for New Mothers. J Public Health Manag Pract. 2023;29(5):663-70. ***A useful guide to those who may want to develop chatbots to provide advice, with an interesting consideration of providing information to under-served communities.***

***** 24. Han R, Todd A, Wardak S, Partridge SR, Raeside R. Feasibility and Acceptability of Chatbots for Nutrition and Physical Activity Health Promotion Among Adolescents: Systematic Scoping Review With Adolescent Consultation. JMIR Hum Factors. 2023;10:e43227. ***The feedback of an adolescent focus group provides important guidance on how young people want to use apps.***

***** 25. Braga BC, Nguyen PH, Aberman NL, Doyle F, Folson G, Hoang N, et al. Exploring an Artificial Intelligence-Based, Gamified Phone App Prototype to Track and Improve Food Choices of Adolescent Girls in Vietnam: Acceptability, Usability, and Likeability Study. JMIR Form Res. 2022;6(7):e35197. ***This paper highlights the importance of considering cultural factors in designing interventions to influence behaviour.***

26. Pervanidou P, Chatzidaki E, Nicolaides NC, Voutetakis A, Polychronaki N, Chioti V, et al. The Impact of the ENDORSE Digital Weight Management Program on the Metabolic Profile of Children and Adolescents with Overweight and Obesity and on Food Parenting Practices. Nutrients. 2023;15(7)

27. Lee C, Kim S, Kim J, Lim C, Jung M. Challenges of diet planning for children using artificial intelligence. Nutr Res Pract. 2022;16(6):801-12.

***** 28. Carrilho TRB, Silva NJ, Paixão ES, Falcão IR, Fiaccone RL, Rodrigues LC, et al. Maternal and child nutrition programme of investigation within the 100 Million Brazilian Cohort: study protocol. BMJ Open. 2023;13(9):e073479. ***This new cohort can be expected to provide valuable data for machine learning approaches in a large population.***

29. Banjar HR. A Smart Monitoring System for Self-Nutrition Management in Pediatric Patients with Inherited Metabolic Disorders: Maple Syrup Urine Disease (MSUD). Healthcare (Basel). 2023;11(2)

***** 30. Alrige M, Banjar H, Shuaib T, Ahmed A, Gharbawi R. Knowledge-Based Dietary Intake Recommendations of Nutrients for Pediatric Patients with Maple Syrup Urine Disease. Healthcare (Basel). 2023;11(3) ***Example of how machine learning can influence management of specific rare diseases.***

***** 31. Yalçın N, Kaşıkcı M, Çelik HT, Demirkan K, Yiğit Ş, Yurdakök M. Development and validation of machine learning-based clinical decision support tool for identifying malnutrition in NICU patients. Sci Rep. 2023;13(1):5227. ***A case study of an attempt to enhance traditional screening methods with machine learning techniques.***

***** 32. Thanhaeuser M, Steyrl D, Fuiko R, Brandstaetter S, Binder C, Thajer A, et al. A secondary Outcome Analysis of a Randomized Trial Using a Mixed Lipid Emulsion Containing Fish Oil in Infants with Extremely Low Birth Weight: Cognitive and Behavioral Outcome at Preschool Age. J Pediatr. 2023;254:68-74.e3. ***A novel approach to secondary analysis of RCT data which may be applied to a wide range of studies.***