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Advances in artificial intelligence and precision nutrition approaches to improve maternal and child health in low resource settings

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Malnutrition continues to be a major threat to health, particularly maternal and child health in low resource settings, resulting in impairments in cognitive function, growth, and development, and metabolic diseases later in life. Nutritional assessment is a cornerstone of any successful nutrition intervention or program whether in the community or at the clinic. Improved computational power and advances in technology may enable precision nutrition-based approaches for maternal and child health, which can complement current methods for nutritional assessment to identify clinical, biochemical, microbiome-related, social, and environmental characteristics to predict responses to nutritional interventions or programs. Precision nutrition has the potential to complement program monitoring, efficacy evaluation, and ultimately to inform design of interventions to improve maternal and child health.

Malnutrition is an urgent threat to human health and disproportionately affects women of reproductive age, pregnant and lactating women, and children[1–3], due to increased physiological demands to support maternal metabolism, transfer to the fetus, and growth and development. Malnutrition—defined to include undernutrition, such as micronutrient deficiencies ("hidden hunger") and underweight, and overnutrition, including excess adiposity and metabolic diseases—is complex in its etiology and assessment. The double-burden of malnutrition, or the coexistence of both undernutrition and overnutrition—at an individual, household, or population level—adds further complexity to the development of interventions and programs to meet the nutritional needs in these populations[4].

In the context of maternal and child health, particularly low-resource settings such as low- and middle-income countries (LMICs), nutritional interventions include micronutrient supplementation, food fortification, and biofortification approaches, with emphasis on prevention or treatment of acute undernutrition or micronutrient deficiencies at the population level[5–7]. For example, micronutrient supplementation and fortification interventions are among the most cost-effective approaches to improve human health and development, particularly in the context of maternal and child health[5,8]. This is critical as nutrition prior to conception and early in life is a key determinant of health during the first 1000 days of life and beyond[9].

Despite major investments, a recent pooled analysis found 1 in 2 women and children still have at least one micronutrient deficiency[3],

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and 1 in 3 pregnant women (500 million) have anemia, a number that has remained unchanged since 2000[10]. At the same time, a type 2 diabetes mellitus (T2DM) crisis has escalated rapidly particularly in LMICs including in South Asia[11]. Progress on the Sustainable Development Goals, particularly Goal 2: Zero Hunger, has stagnated or regressed[12], and progress on reduction in anemia is not on track to meet the World Health Assembly target (i.e., 50% reduction of anemia in women of reproductive age by 2025)[13]. Comprehensive strategies to address all forms of malnutrition—that involves both preventive and therapeutic strategies requiring population and/or setting-specific considerations—are urgently needed that are tailored (where appropriate and feasible) to the individual context including biology, genomics, and environment for maximal impact on improving maternal and child health.

Value addition of precision nutrition: assessment and prediction

Nutritional assessment—to identify or prioritize those at risk or with greatest need for interventions and monitoring response—is a critical component of any successful intervention/program, at the community or the clinical levels. Accurate assessment of nutritional status, such as anthropometric, biochemical, clinical, and dietary data, in women, infants, and children is necessary to monitor existing programs, identify gaps, and measure efficacy of interventions. Precision nutrition–using individual-level data to predict how a given person may respond to a nutritional intervention, and tailor the intervention (e.g., optimal diet) for that individual as opposed to a one-size-fits-all, population-level approach, is a next step after assessment[14]. In addition to anthropometric, biochemical, clinical, and dietary data, and socioeconomic, psychosocial and environmental data[14], other factors that are now possible to measure on a larger scale include genetic, metabolic, proteomic, or microbiome signatures, which may predict the response to specific nutritional interventions[15–17]. Given how maternal factors (e.g., diet, inflammation, microbiome) appear to dynamically shape child health outcomes via shared biomarkers, vertical microbiota transmission, particularly in the first 1000 days of life, AI modeling approaches that can jointly predict outcomes across the mother-child dyad are critical to successful precision nutrition approaches.

Precision nutrition has shown promise in adults, particularly in research from higher income settings, and this is reflected by recent investments to investigate precision nutrition in even larger cohorts to account for more individual-level heterogeneity. Zeevi (2015) and Korem (2017) and colleagues found that integrating most or all of these variables improved prediction of an adult individual's glucose response to a particular food[18,19]. This has set the stage for larger studies such as Nutrition for Precision Health (NPH), part of the by the All of Us study and funded by the National Institutes of Health (NIH)[20]. NPH will help establish which components of precision nutrition need to be measured in adults across the United States and inform nutritional assessment and interventions to improve human health and address key challenges in precision nutrition. The generalizability of these findings to populations in other settings with different metabolomes, microbiomes, and host genetics is still an open question. Some of the challenges pertain to how to better understand and model the multiple and multi-level risk factors for adverse health outcomes to inform care, prevention, and treatment guidelines. Further challenges include limitations associated with implementing AI methods in precision nutrition in low- and middle-income settings, including incomplete or poor-quality data, technological infrastructure gaps, lack of digital literacy, and ethical and regulatory considerations.

Herein, we discuss the implications of using a precision nutrition lens to improve nutritional assessment with a focus on maternal and child health, particularly in low resource settings. We then outline examples of where a precision nutrition approach is being applied in maternal and child health. Finally, we review the technological landscape supporting precision nutrition to identify potential areas to complement conventional practices, with an emphasis on nutritional assessment, screening, and interventions to improve maternal and child health. These are summarized in Fig. 1.

Assessment of nutritional status

Nutritional assessment includes anthropometric measures and body composition, biochemical markers, clinical signs and symptoms, and dietary intake. These are measured and analyzed through direct measures of the body, blood collection and analysis, clinical exams, and interviews with trained personnel. Such methods have been used for decades in nutrition research and have resulted in major gains in the evidence base for nutrition and maternal and child health. However, these methods for assessment are time-, personnel- and resource-intensive, and depend on the availability of trained staff and equipment to collect and process the data, which can range from relatively simple (e.g., body weight data in a small study) to large and complex (e.g., 24-h recall data and food composition databases from repeated samples in a large cohort of mother-infant dyads)[21]. These methods may be complemented by integrating novel approaches to leverage increased computational power and efficiency to analyze complex multi-modal data, via *artificial intelligence* (AI) and *machine learning* (ML) models[16,22]. AI involves using a computer to model intelligent behavior with little human guidance[23]. ML is a mathematical tool that facilitates the development of algorithms to make accurate predictions from large datasets with greater accuracy than traditional statistical methods, and is of increasing interest to nutrition and health research[22,24,25]. Incorporating novel AI and ML methods to nutrition assessment could enable faster, more efficient, and more accurate data, translating to more accurate models and findings and inform the development and monitoring of nutritional interventions, including for maternal and child health.

Anthropometry and body composition

Established methods for nutritional assessment, including anthropometry and body composition, using measurement tapes, length/height boards, and skinfold calipers, are time-intensive and challenging to perform; require trained personnel (and may have high level of inter- and intra-rater variability in measurements); and do not automatically store data digitally, necessitating an additional data entry step[26–28]. For body composition assessment, gold standard methods include dual-energy X-ray absorptiometry (DXA), densitometry, or air displacement plethysmography (bioelectric impedance analysis (BIA),reviewed in refs. 29,30 may not be suitable for pregnant women or children), and require equipment that is costly to purchase and maintain controlled conditions, and may be less feasible in field or resource-limited settings[31].

As optical imaging devices have become relatively inexpensive over the past few decades, interest in digital or automated measures of anthropometry and body composition has increased[27]. Three-dimensional scanning devices can objectively and relatively quickly measure the body, process the acquired data, and calculate circumferences, volumes, lengths, and surface areas[27], although estimation of body composition measures (e.g., fat mass, fat free mass) from this data is more challenging[32]. A 3-dimensional (3D) scanner can complete hundreds of anthropometry measures in seconds[32], though 3D imaging scanners vary in portability[33]. Smartphone and mobile phone-based technologies have advanced such that automated optical scanning systems[33] and BIA[34–36] may be captured via mobile phone, in addition to 2D images taken by the phone's camera. These portable methods could be developed and validated for data collection in field settings at the point of need[30].

Machine learning approaches are well-suited to process data from images from 3D scanners or camera-enabled mobile devices to estimate anthropometry and body composition given that (a) image data analysis can be automated reducing personnel time required; and (b)

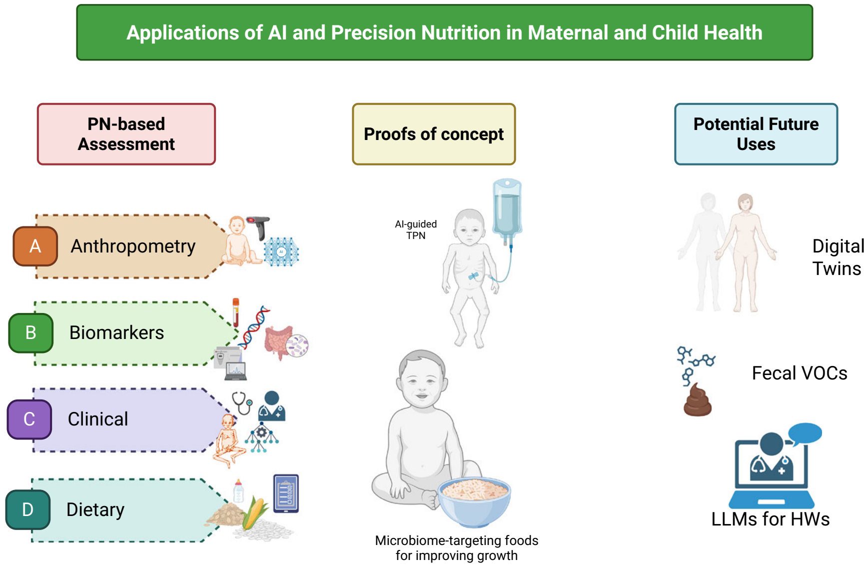

Fig. 1 | Applications of artificial intelligence (AI) and precision nutrition (PN) in maternal and child health. AI and machine learning (ML) have been used in maternal and child health, particularly image-based assessment methods for (A) Anthropometry and body composition measures and (C) Clinical applications such as predicting intra-uterine growth restriction based on demographic and health characteristics. Past uses of AI and ML to define potential novel (B) Biomarkers for nutrient intakes, such as gut microbial signatures[66] have the potential to be applied in maternal and child health, and app-based assessment of (D) Dietary intakes has been successful particularly in estimating most macronutrients among adolescents in a low-resource setting[89]. Two examples where PN-based methods in maternal and child health have been used include "total parenteral nutrition (TPN) 2.0" for neonates in neonatal intensive care units[90] and microbiome-targeting foods in the context of moderate acute malnutrition (MAM)[91]. Finally, we show potential applications for AI/ML-based approaches in maternal and child health, including digital twins, fecal volatile organic compounds (VOC) for predicting mortality in children with severe acute malnutrition (SAM)[96], and the use of large language model (LLM)-powered coaching for frontline health workers' (HW) training on early childhood development curricula[102]. Figure created in BioRender (Huey S, Sinha S, Mehta S (2025) https://BioRender.com/fn7t1bw) and finalized via All Time Design.

the algorithm "learns" or becomes trained and accuracy is increased as additional curated data are ingested[37]. In addition, taking photos of participants is faster and less labor-intensive than anthropometry or body composition measurements, with contactless data collection. For example, ML methods have been used to predict body height from single-depth images in adults by researchers such as Lokshin and colleagues[38] and in multiple studies[39,40]. In children, height measurements and predictions can be used to detect stunting; a 2021 study in India found that a convolutional neural network-based method accurately predicted the height of standing children under 5 years of age within an acceptable 1.4 cm range among 70% of depth images, which were generated from videos from captured on a commercial 2016 smartphone; however, details on the degree of inaccuracy of the remaining 30% of depth images was not reported[41]. However, image and video quality are key for accurate modeling; indeed, videos with noisy data (e.g., blurry, dark, lack of the subject, or too many participants) were identified and removed from the test datasets[41]. In adults ($n = 12$ females and $n = 15$ males) with obesity, a 2022 study found that an automated machine learning method analyzing data from smartphone camera-enabled capture and analysis of 2D images was able to reproducibly and accurately estimate whole body fat mass compared to DXA (correlation $R^2 = 0.99$)[24], with no differences by sex. However, estimating body composition in children using image-based machine learning techniques and validating such tools in the field in pregnant women and young children remain research gaps.

Deep learning algorithms can help process images and videos but require secure server availability for app-based intake estimation for sustainability. In the future, use of convolutional neural networks or other architectures such as generative adversarial networks and deep learning algorithms will be key to process the large image-based datasets. The increased computing power helps to identify more minute details in the pictures and in the process improves accuracy[42]. Current methods for anthropometry and body composition assessment are constrained by high throughput. Advancing the technology to enhance reliability and reproducibility, and to optimize for individuals across the life cycle in the form of a mobile phone are important for monitoring changes in individual anthropometry or body composition over time in resource-limited settings, to develop and evaluate nutritional interventions and programs.

Biochemical

Nutritional biomarkers such as those measured in blood or urine to quantify dietary intake or nutrition status are objective and less prone to bias due to recall or reporting[43]. For example, minerals and vitamins can be measured in blood, stable isotopes of doubly labeled water and urine samples can enable measurement of daily total energy expenditure, and 24-h urinary nitrogen can estimate protein intake[44,45]. One of the main challenges in assessing nutritional status is the limited range of biomarkers that reflect intake and predict functional or clinical outcomes, such as the response to a given dietary intervention in a population. Biomarkers of nutrients and associated metabolites often reflect recent intake rather than sustained dietary habits; adding to this complexity, the metabolic rate for energy and different nutrients has been shown to have inter-individual variation[46,47], possibly due to the gut microbiome[18,48]. In addition, some biomarkers may not accurately reflect status for nutrients that are tightly regulated, such as serum calcium or zinc[49,50], in addition to changes in status prompted by inflammation (described below); finally, a limited range of nutritional biomarkers predict functional outcomes or health outcomes.

The interplay of inflammation and nutritional status may influence intra- and inter-individual variation[51]. The acute phase response involves the release of inflammatory cytokines such TNF-alpha, IL-1, and IL-6, which stimulate the liver to produce acute phase proteins (APP). The APPs include over 200 plasma proteins, an estimated 50% of which are involved in regulation of nutrient transport or status[52]. For example, serum/plasma ferritin (stored iron), retinol (vitamin A status), and zinc (zinc status) are directly affected by inflammation, both acute and chronic. In the context of acute inflammation, serum/plasma ferritin concentrations increase, whereas retinol and zinc decrease[52,53]. Iron trafficking may be impacted[54], limiting the distribution of iron from blood to cells throughout the body in order to limit its availability to pathogens[55]; the liver halts the release of retinol and its binding protein[49]; and the transfer of zinc from blood to liver may increase[50]. As a result, assessment of these micronutrients without accounting for inflammation (e.g., C-reactive protein (CRP), α−1-acid glycoprotein (AGP) or other inflammatory cytokines[56]) may result in altered (higher or lower) micronutrient status[57].

Several methods are available for population-level adjustment of ferritin and retinol, including Biomarkers Reflecting Inflammation and Nutritional Determinants of Anemia (BRINDA); however, not all micronutrients or populations are covered; BRINDA adjustment methods are available for or validated in preschool children, school-aged children, or women of reproductive age (ferritin only), but not in pregnant women or infants[53,58–61]. These methods use CRP and/or AGP to adjust micronutrient status to a more accurate concentration without the presence of inflammation. However, these are population-based methods for inflammation adjustment and do not typically apply to the individual level and in the context of illness. Considering that both acute *and* chronic inflammation (e.g., obesity and metabolic diseases) appear to impact micronutrient concentrations, accounting for inflammation as part of the comprehensive set of variables is important for precision nutrition-based strategies. These biomarkers related to metabolism (metabolites) are part of nutrient metabolism. Metabolomics, the study of these metabolites or unique fingerprints as a result of metabolic processes is an upcoming theme in nutrition research. Recently, ML methodologies such as neural networks were used to prepare an evaluation chart using nutritional biomarkers and tried to link dietary intake with biochemical profile to understand the effect on body weight[62]. A further challenge is to capture intra- and inter-individual variation in the metabolic and phenotypic response to a dietary intervention and ultimately predict those most likely to respond to a particular type of intervention.

Assessment of biological specimens requires central laboratories, specialized equipment, ensuring cold chain, extensive benchmarking and validation of preservation methods, and trained personnel. Methods and devices that are field-friendly (i.e., portable and not impacted by variation in environment such as temperature and humidity) and that adhere to the ASSURED criteria (i.e., Affordable, Sensitive, Specific, User-friendly, Rapid and robust, Equipment-free, Delivered)[63] are particularly relevant in the context of maternal and child health and in lower-resource settings. Additionally, the availability of noninvasive methods or tests that require only small volumes of blood—particularly appropriate for populations like young children and pregnant women—is paramount to successful assessment and monitoring. Biomarker assessment at the point of care has considerable applications for screening and precision nutrition in the context of maternal and child health, particularly in resource-limited settings. For example, point-of-care assessment of vitamin A status in blood has been demonstrated, using chemical reaction that can be miniaturized in a device or test kit to facilitate use in field and community healthcare settings. Methods to screen for vitamin A status using point-of-care methods have been cataloged previously and include portable fluorometers, photometers, immunoassays, and microfluidics-based though only some were commercially available[64]. These devices have the potential to routinely screen for vitamin A deficiency—and evaluate interventions—particularly in settings with limited resources and infrastructure.

Gut microbiome diversity, composition, and function are also potential novel biomarkers of dietary intake, dietary quality[65], nutrition status, and/or response to interventions, including analysis of fecal microbial biomarkers of food intake using AI methods[66]. These methods need to be implemented and validated in the context of maternal and child health, including during pregnancy, mother-infant dyads, and in children. Diversity in maternal and child populations including ethnicity, habitual diets, socioeconomic status, and age is needed for these types of studies as well as other studies such as those using gut microbiome to predict glycemic response to interventions. Validation across large, diverse populations and over time, as well as repeated analyses among similar cohorts, is needed to ensure reproducibility. In addition, evaluation of novel biomarkers compared to currently used biomarkers. For these biomarkers to accurately reflect dietary intake, further detail is needed regarding food and nutrient composition, since vitamin and mineral content in vegetables varies considerably[67] depending on conditions such as season[68] or post-harvest processing and storage[69]. Standardized approaches for biomarker validation, comprehensive and accessible food composition databases, a common ontology for dietary biomarkers, and advances in statistical procedures for novel biomarkers of dietary intake are also needed[45].

Clinical

Clinical outcomes include adverse pregnancy outcomes, and metabolic diseases, including cardiovascular disease (CVD), T2DM, metabolic dysfunction-associated steatotic liver disease (MASLD, formerly known as non-alcoholic fatty liver disease (NAFLD)), obesity, hyperlipidemia, and cancers[70,71]. The physiological changes that occur during pregnancy and the postpartum period may unmask metabolic risk factors such as hypertension and altered glucose metabolism not observed prior to pregnancy, highlighting a key window to use AI methods to monitor risk factors and future cardiovascular outcomes[72]. In children and adolescents, the prevalence of obesity continues to rise, particularly in low- and middle-income settings, and is linked to persistence of obesity into adulthood and associated comorbidities and premature mortality[73].

The applications of ML and AI methods in clinical examination may enable earlier intervention or treatment, particularly for nutrition-related metabolic and non-communicable diseases. Many metabolic diseases and sequelae may be assessed via medical imaging techniques, which are particularly suitable to ML and AI methods[72,74,75]. For example, AI-based processing and assessment of retinal images enabled early detection of retinopathy related to T2DM[76]. Training ML models on MRI-derived images of liver fat content along with other 'omics and clinical data have also been used to diagnose NAFLD and outperformed existing prediction tools[77]. Other AI methods such as convolutional neural networks can model raw electrocardiogram signatures to detect heart rhythm dysfunctions[72]. They may also be useful for detecting pregnancy outcomes such as congenital anomalies and intrauterine growth retardation (IUGR)[78,79].

The most accurate method for measuring low-density lipoprotein (LDL) requires beta-quantification, which is time-intensive, expensive, and infrequently used. The Friedewald equation was developed to estimate LDL using total cholesterol (TC), high-density lipoprotein cholesterol (HDL-C), and triglycerides (TG): $LDL\text{-}C = TC - HDL - TGs/5$[80]. However, this equation relies on the assumptions that have not been validated in pregnancy, in children, or in the context of certain health conditions, such as HIV[80]. Five ML methods —linear regression, random forest, gradient boosting, support vector machine (SVM), and neural network—were used to estimate LDL-C in women with HIV (n = 5,219) or without HIV (n = 2127) compared to the Friedewald equation[80]. In this study, an SVM algorithm outperformed the other four ML methods and the Friedewald equation. Initial findings from this study offers support for further investigation of ML methods in predicting risk factors for metabolic health outcomes.

In a study using a Bayesian kernel machine regression (BKMR) ML approach, sex-specific differences were observed when 12 dietary components were examined in association with 10-year risk of atherosclerotic CVD[81]. BKMR was used to incorporate non-linear and interactive associations of dietary components with health outcomes, and account for the high degree of collinearity often observed with dietary intakes. When all other dietary components were held fixed, unprocessed red meat was associated with increased risk for atherosclerotic CVD in women. In men, fruit was non-linearly associated with lower risk atherosclerotic CVD, with an interaction between fruit consumption and whole grains was reported. BKMR identified complexities with multiple dietary intakes in association with CVD and indicate its potential in identifying which nutrient(s) or their interaction(s) are associated with disease risk by sex. Together, these methods enable more targeted precision nutrition approaches or interventions to be developed.

The potential clinical applications for machine learning in the context of precision nutrition and non-communicable diseases is evident, particularly to automate and standardize analysis of medical images. The applications of ML methods to identify risk factors or health outcomes may vary in the clinical context. For example, while there is at least one FDA-approved AI-based device available for diabetic retinopathy screening in adults, which analyzes retinal images using a cloud-based software program to output a positive or negative result[82], other clinical outcomes (e.g., CVD and MASLD) are in the development stage and require validation and refinement, Further development and validation of AI and ML methods is needed for early detection of non-communicable diseases to inform early intervention and treatment.

Dietary records

Dietary intake has been identified as a modifiable determinant of individual nutritional status. Current methods for estimating dietary intake include 24-h dietary recall, food frequency questionnaire, multiple-day food records or diet records[83]. Although self-reported dietary intake has been evaluated using these methods in numerous epidemiological studies, measurement error, day-to-day variability, and intensive training, resources, and time burden for personnel and participants are important limitations. Food composition databases for estimating the macro- and micro-nutrient content and intake of, for example, a 24-h recall, may be limited. For example, in one study, half of the available ~100 food composition databases globally were last updated more than 10 years ago with some only available for 1980-1989, limiting the data on data such as ultra-processed foods[84].

It is important to develop and validate methods for accurate dietary intake in pregnancy and during critical periods such as preconception, pregnancy, and early in life. Methods such as wearable devices[85–87], image-based assessment[88], and novel biomarkers[66] may be used to accurately capture dietary intakes. For example, ML methods has been used to determine a gut microbial signature of specific whole foods (e.g., broccoli, nuts, barley) in men and women[44,66]. However, these methods may require additional expertise and time in processing and analyzing the resulting data[88]. In order to address the gap of dietary intake of adolescent females in low- and middle-income settings, a mobile AI-technology–assisted dietary assessment technique, the "Food Recognition Assistance and Nudging Insights" (FRANI) app was developed and validated against weighed food records as a ground truth in Vietnam[89]. Dietary intake was assessed on three nonconsecutive days (i.e., 2 weekdays, 1 weekend). A smartphone with the FRANI app was provided and participants (12–18 y) were trained to take photos of each instance of food consumption. Equivalence between FRANI and weighed records was determined at the 10% bound for calories, protein, fat, and four micronutrients, and at the 15% and 20% bound for carbohydrate and several other vitamins and minerals, suggesting an accurate estimation of most intakes. Some wider bounds were observed for vitamins A and B_{12}, possibly due to lower frequency of consumption, estimation errors, and large variance, small sample size, and limitations of FRANI in assessing vitamin A-rich fruit and vegetables and vitamin-B_{12}–rich foods in mixed dishes. Other limitations included the need for training, recall bias, changes in eating patterns due to taking photos while eating, and limitations of recognizing less common foods. However, findings demonstrate the potential for AI-assisted dietary intake estimation in the context of maternal and child health, particularly in low-resource settings.

Precision nutrition applied in maternal and child health

In this section, we describe some examples of using precision nutrition approaches to optimize an intervention in a study in infants and children. Advanced AI-based precision nutrition approaches are beginning to be applied in maternal and child health contexts. Engagement of key stakeholders, including scientists, local and public authorities, and healthcare professionals, and incorporation of cultural practices, religion, language, caregiving norms, and family structure into precision nutrition-based recommendations is critical to the success and scale-up of precision nutrition in maternal and child health.

AI-guided precision total parenteral nutrition

Recently, AI methods were used to guide and optimize total parenteral nutrition (TPN) formulas for infants in the neonatal intensive care unit (NICU)[90]. Using information collected routinely in electronic medical records, the AI model "TPN 2.0" identified 15 specific formulas that improved safety, reduced cost, was rated higher by physicians compared to the current practice in a blinded study, and had fewer morbidities such as necrotizing enterocolitis. This model, employed using transformer architecture, may be scaled to LMICs given that the data for the model are already collected as part of the standard of care.

Microbiota-directed complementary food

Microbiota-directed complementary food (MDCF) has demonstrated success over traditional ready-to-use therapeutic food (RUTF), highlighting the utility of a precision nutrition approach using host gut microbiome as an input variable[91,92]. RUTFs were designed to treat SAM in children; tailoring for gut microbial composition may be an important additional therapeutic target. Intervention with MDCF twice daily for 3 months increased the abundances of plasma proteins associated with improved growth, bone health, immune function and neurodevelopment in malnourished children in Bangladesh, compared to standard RUTF. Clinically, the mean rate of growth per week was greater in the MDCF group (WLZ; MDCF: 0.021 (0.014, 0.029) vs. RUTF: 0.010 (0.003, 0.017), and specific gut bacteria correlated with WLZ were increased. This intervention was given for only 3 months; longer follow-up studies will determine if this improved growth is sustained over time. Findings are consistent with recent studies in adults that have demonstrated that outcomes of dietary interventions depend on the baseline gut microbiome of the host, which varies by individual[18,19]. Tailoring diets with microbiome-targeting or directed foods for addressing nutritional and health challenges in children and adults is warranted.

Potential for precision nutrition in maternal and child health

Digital twins

Digital twins are virtual systems (or replicas of machines) used to simulate how a product may be optimized by adjusting one or multiple factors—in a software environment[93,94]. Originating in engineering, and similar to the counterfactual in epidemiology, the concept of digital twins is increasingly being applied to medicine (e.g., "patient-specific digital twins"). Patient data, collected from the whole body to the subcellular level, can be collected and ingested into devices or algorithms, which calculate for example, the amount of insulin to deliver from an implanted glucose sensor, or risk assessment for thrombosis from clinical measurements[93]. The concept of "digital twins" is a promising approach that involves integrating biological data from the whole-body to the subcellular level with clinical data from patients. Findings can be used for precision nutrition and medicine to tailor and individualize treatment. The integration of AI for precision nutrition, to predict individual response to a given intervention holds promise, particularly in extending the reach of traditional health care systems in maternal and child health and in low-resource settings. Integration of digital twins into existing healthcare systems needs to address computational complexity, and to tailor nutrition interventions to pregnant women and their children.

Use of fecal volatile organic compounds as a biomarker of gut microbiota composition

Microbiome signatures could be a novel bioindicator to predict response to nutritional interventions. Fecal volatile organic compounds may predict intestinal microbiota composition and metabolic function, given that these compounds are produced in the gut primarily by intestinal microbes as part of the fermentation of non-starch polysaccharides[95]. Volatile organic compounds (VOCs) can be measured using a commercial portable, self-contained unit[96]. For example, a recent study in Malawi and Kenya demonstrated that these compounds predicted mortality among hospitalized children with severe acute malnutrition[96]. In this study, a pipeline of machine learning classifiers were used to compare fecal volatile organic compounds of the children, finding that these profiles were distinct between children who survived and those who died (area under the curve = 0.71), likely reflecting differences in the gut microbiota, although sequencing was not conducted to confirm. The SVM algorithm best predicted child mortality in this study. However, prediction via VOCs is challenged by variability in VOC composition across individuals, standardization issues, and practical application constraints. Further research is needed to inform assessment of VOCs as a biomarker in nutrition studies, to determine or describe normal profiles of VOCs and validate the biomarker in different populations.

Use of plasma proteomics for assessment of anemia and micronutrient deficiencies

The etiology of anemia and micronutrient deficiencies are complex and multifactorial. Hence, a holistic approach is needed to for screening and interventions for prevention and treatment. Validated biomarker panels for micronutrient status assessment is needed to inform screening and interventions in the context of maternal and child health and in low-income settings. In this context, identification and quantification of plasma proteomics[97] could help support screening quantification of protein biomarkers of micronutrient status in undernourished children in low- and middle-income settings[98]. These approaches require minimal sample size and are well-poised to screen for multiple micronutrient deficiencies and inflammatory biomarkers at a time in a single platform[99]. Determination of the precise cluster of plasma proteins is needed to precisely assess micronutrient and inflammation status, which may be possible via machine learning, and to develop a field-friendly affordable biomarker panel for the assessment at the population level.

Use of deep learning and artificial intelligence for disease diagnosis

Small bowel enteropathies (e.g., Environmental Enteric Dysfunction (EED), celiac disease, tropical sprue, and HIV enteropathy) account for a significant proportion of undernutrition in children in low-income settings. Deep learning and AI-based approaches can be used for screening and diagnosis of small intestinal enteropathies. Histopathology is the gold standard for the diagnosis of all these conditions, but with significant overlaps such as villous blunting and crypt elongation. The application of convolutional neural networks for image analysis demonstrated accuracy in the diagnosis of EED and celiac disease[100]. The use of deep learning methods on the images obtained by video capsule endoscopy is another example of AI-based application for disease detection[101]. However, more precise tools or approaches are needed to diagnose enteropathies to mitigate the nutrition-related burden and consequences.

LLM-powered coach training frontline health workers on early childhood development curricula

In South Africa, LLMs, a form of artificial neural network based on generative AI, are being developed to support frontline health care workers[102]. These LLMs will distill information and content on early childhood development and the Kangaroo Mother Care method, promoting skin-to-skin contact and self-care for exclusive breastfeeding, particularly for infants born preterm or low birth weight[103]. The curriculums developed by the LLMs will be tested for safety, accuracy, usability, and added value. This is one of 50 innovations recognized by the Bill & Melinda Gates Foundation Grand Challenges Initiative to harness LLMs to reduce global inequality.

Limitations and challenges of using AI in maternal and child health

There are several limitations and challenges to use of AI in the context of maternal and child health and in resource-limited settings. Methodological limitations include model generalizability, data privacy, and potential biases in the training data. National and regional guidelines are needed for regulatory frameworks for data privacy. Population-specific training datasets are needed for development and validation of algorithms for maternal and child health and in LMICs. Application and feasibility limitations include fitting in AI-based assessments or predictions into already overworked, under-resourced healthcare staff. Identification of key variables that explain inter- and intra-individual variation is needed to inform precision nutrition interventions.

Conclusions

Malnutrition continues to represent a major threat to maternal and child health, particularly in low- and middle-income settings. Precision nutrition methods need to be integrated into screening and interventions for maternal and child health and in LMICs. Further research is needed to establish the benefits of precision nutrition in maternal and child health, particularly in LMICs, which may lack the infrastructure and resources to implement precision nutrition into routine practice, as well as have very different microbiome compositions and diets. In resource-constrained settings, limited clinical, laboratory, and financial resources may constrain routine nutritional assessment and microbiome and phenotyping assessments. While technological advances are driving the cost of these innovations down, recent advances in laboratory and quantitative methods and technologies can enhance accessibility at the point of care. Further, precision nutrition approaches need to socio-cultural contexst, preferences, and the food environment. Privacy concerns will need to be addressed, particularly considering the novel methods with optical imaging and body composition. With computational power widely accessible and increasingly more affordable around the world, an AI and ML approaches may democratize the practice of public health and medicine far more rapidly than other methods. Precision nutrition—and integration of AI and ML methods and improved computational power and technological advancements—needs to be integrated to nutritional screening, diagnosis, and treatment, and inform the development of nutritional interventions to improve maternal and child health. Precision nutrition approaches can help enhance the design, monitory, and evaluation of interventions to improve maternal and child health.

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Author contributions

S.M., J.L.F.: Supervision, conceptualization, writing—review & editing; S.L.H., S.M.F., K.R.: Writing—original draft; S.L.H., S.S.: Writing—review & editing, visualization; T.A.: Critical review; R.K.: Writing—review & editing.

Competing interests

R.K. is a scientific advisory board member, and consultant for BiomeSense, Inc., has equity and receives income. He is a scientific advisory board member and has equity in GenCirq. He has equity in and acts as a consultant for Cybele. He is a co-founder of Biota, Inc., and has equity. He is a cofounder of Micronoma and has equity and is a scientific advisory board member. He is a board member of Microbiota Vault, Inc. He is a board member of $N = 1$ IBS advisory board and receives income. He is a Senior Visiting Fellow of HKUST Jockey Club Institute for Advanced Study. The terms of these arrangements have been reviewed and approved by the University of California, San Diego in accordance with its conflict of interest policies. All other authors declare no competing interests.

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