

Artificial Intelligence-Driven Personalized Nutrition and Nutraceutical Strategies for Gut Microbiome Health**Diksha Sharma¹, Prashant Rojaria², Aditee Jangid³, Pawan Kumar Basniwal⁴****^{1,2}Scholar, Sri Balaji College of Pharmacy, Jaipur, Rajasthan, India****³Assistant Professor, Sri Balaji College of Pharmacy, Jaipur, Rajasthan, India****⁴Professor & Principal, Sri Balaji College of Pharmacy, Jaipur, Rajasthan, India****Corresponding author: Diksha Sharma****Conflict of interest: No conflict of interest****Abstract:**

The human gut microbiome is a dynamic and highly individualized ecosystem that regulates digestion, metabolism, immunity and gut–organ communication. Diet is among the most powerful modifiable determinants of microbiome composition and function, and this bidirectional diet–microbiota relationship underlies growing interest in nutraceuticals—probiotics, prebiotics, synbiotics, postbiotics and polyphenols—as tools for modulating gut health. However, inter-individual variability in microbiome composition, metabolism, genetics and lifestyle means that a single dietary or nutraceutical strategy rarely produces uniform outcomes, creating a strong rationale for personalized nutrition. Artificial intelligence (AI) and machine learning (ML) offer a powerful analytical framework for integrating multi-omics, dietary and clinical datasets to predict individual responses and guide targeted interventions. This narrative review synthesizes current literature on the gut microbiome, diet–microbiota interactions, nutraceutical modulation of gut health, and the emerging role of AI in personalized nutrition and nutraceutical selection, while critically examining applications, limitations and future directions for precision gut healthcare.

Keywords: gut microbiome; personalized nutrition; nutraceuticals; artificial intelligence; machine learning; precision healthcare; multi-omics.

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Introduction

The gastrointestinal tract harbours a complex and dynamic community of bacteria, archaea, fungi and viruses collectively termed the gut microbiome. This ecosystem is shaped by diet, lifestyle, genetics, environment and medication exposure, and contributes to digestion, metabolic regulation, immune function and intestinal homeostasis through microbial metabolites such as short-chain fatty acids (SCFAs).

Alterations in microbial composition or function—gut dysbiosis—have been associated with metabolic, cardiovascular, gastrointestinal and neurological conditions, although these associations are complex and individual-specific.

Nutrition is a principal modifiable factor influencing the microbiome: dietary substrates shape microbial growth and metabolite production, while microorganisms transform dietary compounds such as polyphenols into bioactive metabolites. This bidirectional relationship has fuelled interest in nutraceuticals (probiotics, prebiotics, synbiotics, postbiotics and polyphenols) as tools for supporting gut health. Because individual responses to the same

intervention vary considerably, personalized nutrition—which incorporates microbiome and multi-omics information into individualized dietary strategies—has emerged as a logical extension of nutraceutical research. Advances in sequencing (16S rRNA, shotgun metagenomics) and multi-omics technologies (metatranscriptomics, metaproteomics, metabolomics) generate large, multidimensional datasets that are difficult to interpret using conventional statistics. Artificial intelligence and machine learning provide the analytical capacity to detect complex patterns across such datasets, positioning AI as a potential bridge connecting individual biological data with targeted nutritional and nutraceutical recommendations. This review synthesizes the current evidence base and critically evaluates opportunities and limitations of AI-driven, microbiome-informed personalized nutrition.

Review Methodology

This article was structured as a narrative review with a systematic literature-search component. Searches were conducted across PubMed/MEDLINE, Scopus, Web of Science, ScienceDirect and Google Scholar

using combinations of the terms "gut microbiome," "personalized/precision nutrition," "nutraceuticals/probiotics/prebiotics/postbiotics," "artificial intelligence/machine learning/deep learning" and "multi-omics." Peer-reviewed reviews, clinical studies and key original research addressing the microbiome, diet–microbiota interactions, nutraceuticals, AI applications or multi-omics integration were included; duplicates, non-scientific sources and articles lacking sufficient scientific detail were excluded. Study selection broadly followed PRISMA principles (identification → screening → eligibility → inclusion), and extracted data were organized by author/year, study type, research area, intervention, AI approach, major findings and relevance to personalized gut healthcare.

Gut microbiome–host interaction pathway

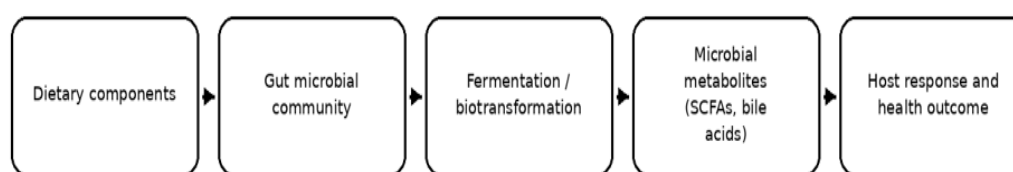


Figure 1. Proposed gut microbiome–host interaction pathway linking diet, microbial metabolism and host outcomes.

Nutrition and the Gut Microbiome

Dietary fibre, fruits, vegetables and fermented and polyphenol-rich foods generally provide fermentable substrates that support beneficial microbial activity and SCFA production, whereas diets high in processed foods, refined carbohydrates and fat may alter the microbial environment

unfavourably. Effects depend on overall dietary pattern rather than single nutrients (Table 2). Because individuals differ in baseline microbiome composition, genetics and metabolism, identical diets can produce different microbial and metabolic outcomes—the central rationale for microbiome-informed personalized nutrition.

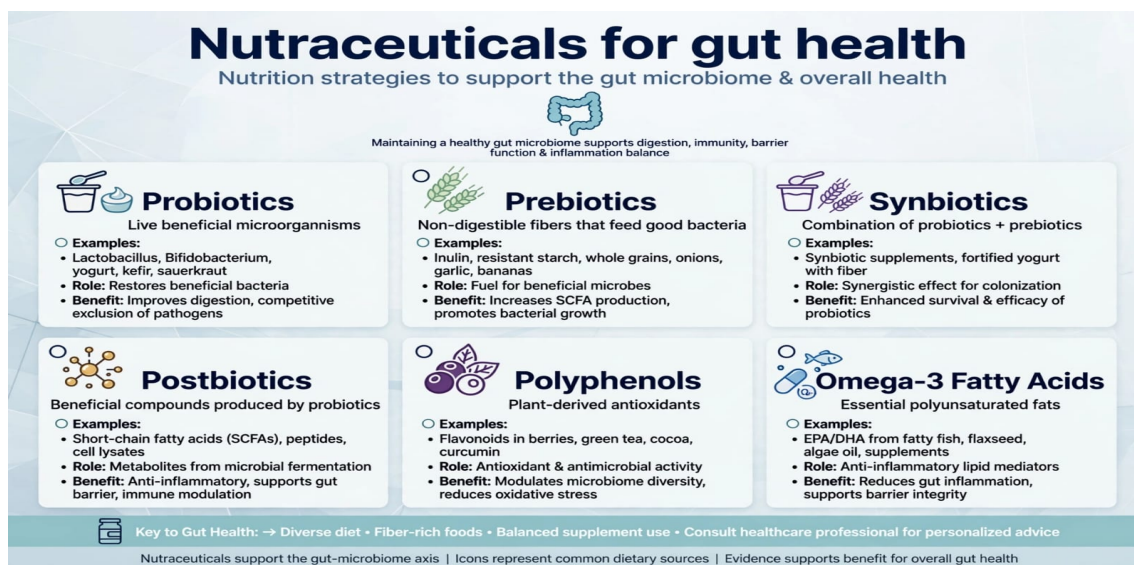


Figure 2:

Nutraceuticals for Gut Health

Probiotics (live beneficial microorganisms, e.g., *Lactobacillus*, *Bifidobacterium*), prebiotics (selectively fermented substrates such as inulin), and synbiotics (combined probiotic–prebiotic formulations). postbiotics (inanimate microbial preparations/metabolites) and polyphenols each modulate the microbiome through distinct but overlapping mechanisms—altering microbial

composition, promoting fermentation and SCFA production, supporting gut-barrier integrity, and modulating host immune and metabolic signalling. Efficacy, however, depends on strain/substrate characteristics, dose, and the recipient's baseline microbiome, diet and host physiology, motivating individualized rather than uniform nutraceutical strategies.

Nutraceutical-mediated gut microbiome modulation

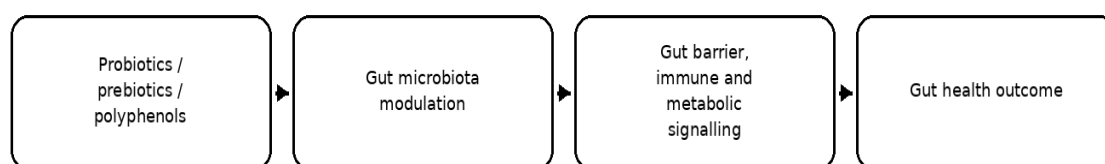


Figure 3. Mechanisms of nutraceutical-mediated gut microbiome modulation.

Personalized Nutrition and the Gut Microbiome

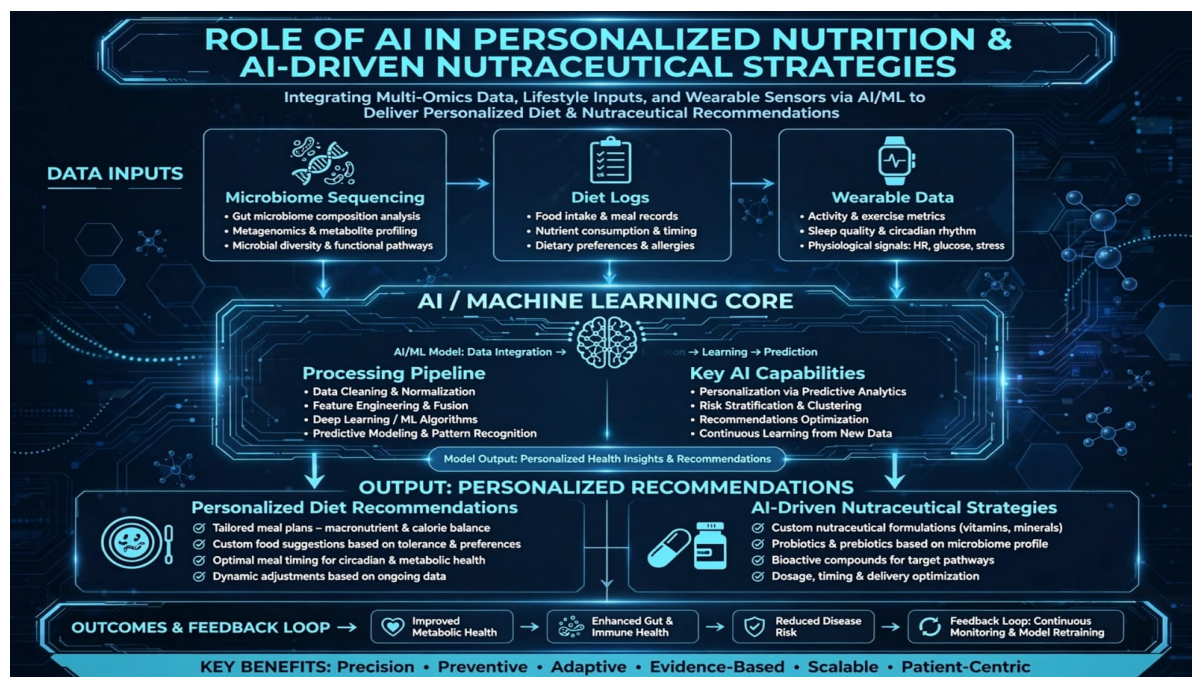
Personalized nutrition adapts dietary recommendations to individual genetic, metabolic, lifestyle and microbiome characteristics rather than relying on population-level guidelines. Because microbial composition determines how dietary substrates are metabolised, identical diets can yield different physiological outcomes across individuals. Multi-omics integration—combining metagenomics, metatranscriptomics, metaproteomics and metabolomics—provides a more complete picture of microbial composition and function than taxonomic profiling alone, but the resulting datasets are too complex for conventional analysis, motivating the application of AI/ML

Role of AI in Personalized Nutrition

AI and ML enable analysis of complex, multi-variable datasets spanning dietary intake, microbiome composition, metabolic parameters and lifestyle information. Applications include AI-assisted dietary assessment (classifying food

records, correcting reporting bias), microbiome analysis (microbial classification, biomarker discovery, disease-pattern recognition), multi-omics integration, and prediction of individual nutritional response. Supervised learning suits defined-outcome prediction (e.g., glycaemic response), while unsupervised learning helps identify naturally occurring microbiome or dietary clusters. Predictive frameworks can be iterative, incorporating follow-up monitoring data to refine subsequent recommendations—moving personalized nutrition from a one-time recommendation toward a continuously adaptive model.

Nonetheless, predictive accuracy does not equal clinical effectiveness; AI outputs require validation through well-designed human studies. Individual data: Diet | Microbiome | Metabolic parameters ↓ AI / Machine Learning analysis ↓ Individual response prediction ↓ Personalized dietary / nutraceutical recommendation ↓ Follow-up monitoring → Model refinement (feedback loop)



AI-assisted personalized nutrition framework

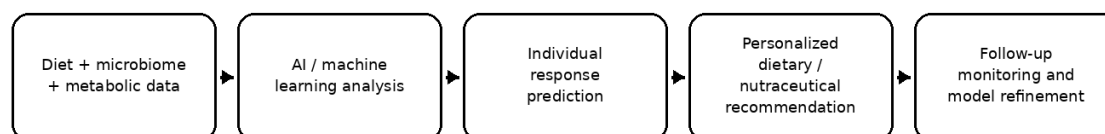


Figure 4. AI-assisted framework for prediction and personalization of nutritional interventions.

AI-Driven Nutraceutical Strategies

AI-based screening can analyse relationships among bioactive compounds, molecular characteristics and biological/microbial targets to prioritize nutraceutical candidates before laboratory validation.

In probiotic/prebiotic selection, ML models could analyse an individual's microbiome profile to identify imbalances and match suitable strains or

substrates rather than applying a uniform recommendation. Personalized nutraceutical selection represents the most direct convergence of AI and precision healthcare, integrating microbiome, dietary, metabolic, clinical, lifestyle and prior-response data into a single predictive model with a feedback loop for continuous refinement.

AI-assisted personalized nutraceutical selection

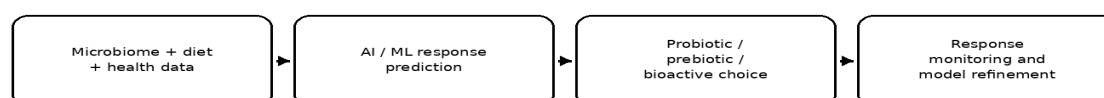


Figure 5. Conceptual framework for AI-assisted personalized nutraceutical selection

Applications in Health and Disease

Metabolic disorders: microbial composition and metabolites are implicated in obesity, insulin resistance and type 2 diabetes; AI can integrate microbiome, dietary and metabolic data to predict response to fibre, probiotic, prebiotic or polyphenol interventions. Gastrointestinal disorders: conditions such as inflammatory bowel disease and irritable bowel syndrome show heterogeneous microbial profiles even within the same diagnosis, creating opportunities for microbiome-informed, AI-guided nutraceutical selection. Gut–brain health: the bidirectional gut–brain axis, mediated by microbial metabolites, immune signalling and neural/endocrine pathways, is an emerging target for AI-integrated dietary and nutraceutical strategies, though this area requires substantially more longitudinal and clinical validation.

Challenges and Limitations

Despite considerable promise, several barriers limit clinical translation: (i) inter-individual variability, requiring diverse, longitudinal cohorts for generalizable models; (ii) data quality/standardization, given inconsistencies in sequencing platforms and dietary assessment protocols; (iii) multi-omics complexity, which demands harmonized analytical pipelines; (iv) AI interpretability, since many models function as "black boxes," necessitating explainable-AI approaches; (v) limited clinical validation, as most evidence derives from small or short-duration studies; and (vi) privacy, ethical and regulatory uncertainty surrounding sensitive microbiome, genetic and digital-health data and the lack of harmonized regulatory pathways for microbiome-responsive nutraceuticals.

Future Perspectives

Future research should combine microbiome profiling, metabolomics, dietary data and host characteristics within explainable AI frameworks that prioritize interpretability and reproducibility alongside predictive accuracy. A key direction is adaptive personalized nutrition, in which continuous monitoring of dietary intake, microbiome shifts and physiological response iteratively refines recommendations (baseline data → AI/ML → personalized intervention → response monitoring → model update). Progress will also depend on high-throughput screening for probiotic and bioactive-compound discovery, microbiome-responsive delivery systems, and multidisciplinary collaboration among nutrition scientists, pharmacists, microbiologists, data scientists and regulators, supported by standardized datasets, diverse populations and rigorously designed clinical trials

Conclusion

The gut microbiome forms a critical biological link between diet, nutraceuticals and human health, and its substantial inter-individual variability provides a strong rationale for personalized, microbiome-informed nutrition. Nutraceuticals such as probiotics, prebiotics, synbiotics, postbiotics and polyphenols offer promising but variably effective tools for gut modulation.

Artificial intelligence and machine learning provide a powerful means of integrating multi-omics, dietary and clinical data to predict individual responses and guide nutraceutical selection, potentially transforming population-level recommendations into adaptive, precision-oriented strategies. Realizing this potential will require overcoming challenges in data standardization, model interpretability, clinical validation, and data privacy/regulatory governance, with success ultimately measured by safe, reproducible and clinically meaningful health outcomes rather than computational accuracy alone.

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