

Bridging the Knowledge–Behavior Gap in Nutrition: The Role of Artificial Intelligence in Addressing Undernutrition and Dietary Behavior Change in India

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Abstract-- Undernutrition remains a persistent public health challenge in India despite extensive knowledge regarding healthy dietary practices and national nutrition programs. The gap between knowing what constitutes a healthy diet and consistently consuming it is driven by complex behavioral, socioeconomic, cultural, and environmental factors. Artificial intelligence (AI) has emerged as a transformative tool capable of bridging this knowledge–behavior gap by delivering personalized, context-aware, and scalable nutrition interventions. AI systems can integrate dietary assessment, predictive analytics, and behavioral nudges to influence food choices, monitor dietary intake, and enable adaptive nutrition education (Figure1). This paper examines the potential of AI-enabled technologies to promote

behavioral change related to undernutrition in India. The manuscript explores behavioral determinants of nutrition, outlines AI-driven solutions such as personalized diet recommendation systems, food recognition technologies, predictive malnutrition risk models, and digital behavior change platforms, and discusses how these innovations can complement existing public health programs. The paper also highlights implementation challenges including digital literacy, data bias, ethical considerations, and infrastructural inequalities. Ultimately, AI has the potential to support precision public health nutrition by transforming passive knowledge into actionable dietary behavior, thereby contributing to the reduction of undernutrition and improving population health outcomes in India.

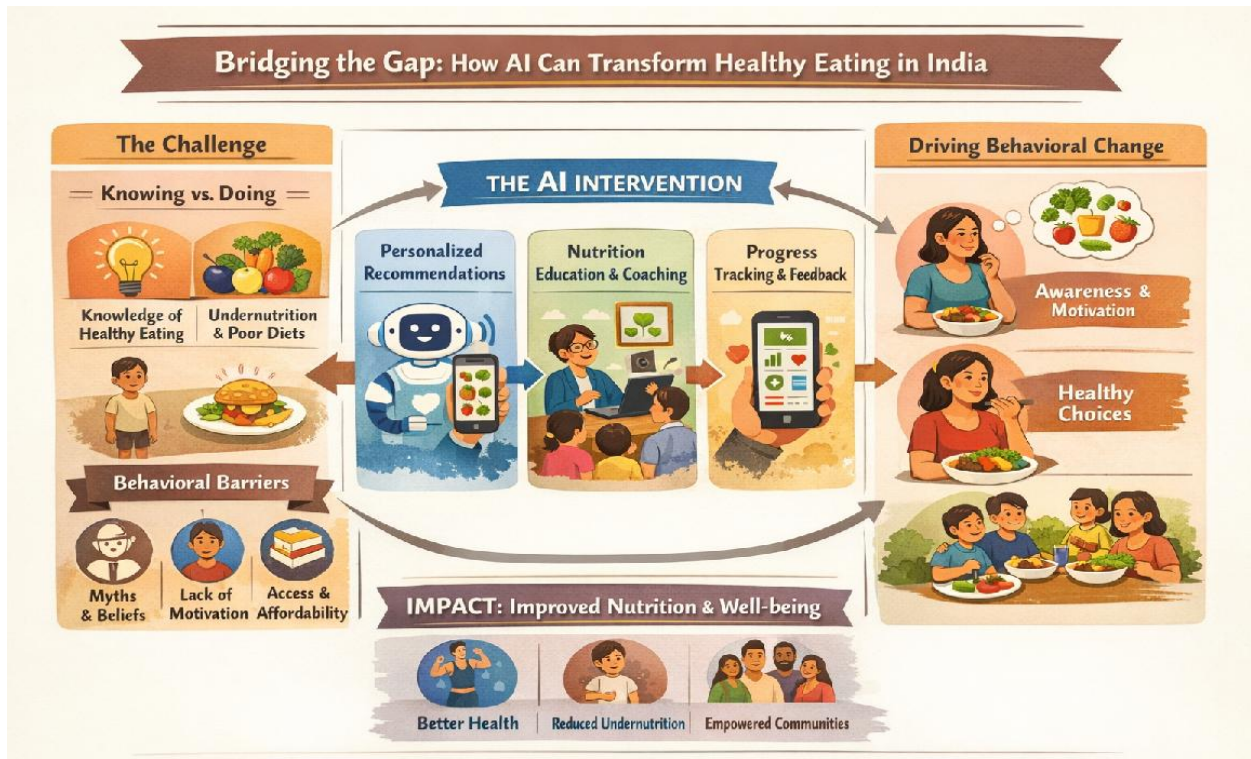


Figure 1. Conceptual Framework: Artificial Intelligence–Enabled Behavioral Pathway to Bridge the Nutrition Knowledge–Action Gap in Undernutrition in India.



Keywords-- Artificial intelligence, nutrition behavior change, undernutrition, digital health, India, personalized nutrition, public health nutrition

I. INTRODUCTION

Malnutrition continues to represent one of the most critical public health challenges globally, particularly in low- and middle-income countries such as India. Despite decades of policy initiatives and nutrition programs, India still faces a substantial burden of undernutrition characterized by high rates of stunting, wasting, and micronutrient deficiencies among children under five years of age and women of reproductive age (Black et al., 2013; International Institute for Population Sciences [IIPS] & ICF, 2021). According to national survey data, a considerable proportion of Indian children remain affected by chronic undernutrition, reflecting persistent gaps in dietary quality, maternal health, sanitation, and access to healthcare services (IIPS & ICF, 2021). Undernutrition during early life has profound consequences, including increased susceptibility to infections, impaired physical growth, delayed cognitive development, and reduced educational attainment (Victora et al., 2008). These effects extend beyond individual health, contributing to long-term reductions in workforce productivity and economic growth, thereby perpetuating intergenerational cycles of poverty and malnutrition (Black et al., 2013; Hodinott et al., 2013). Addressing undernutrition therefore remains a central priority for public health systems, requiring integrated approaches that combine nutrition-specific interventions with broader strategies targeting food security, maternal education, sanitation, and healthcare access.

While nutritional science has generated extensive knowledge regarding balanced diets and dietary requirements, translating this knowledge into consistent dietary behavior remains challenging. The discrepancy between awareness and action—often described as the *knowledge-behavior gap*—is widely documented in nutrition and public health research. Although individuals may possess adequate knowledge about healthy eating, this knowledge does not necessarily translate into sustained dietary change (Parmenter & Wardle, 2000; Spronk et al., 2014). Studies indicate that nutrition knowledge is only one of several determinants of dietary behavior and often interacts with psychosocial, environmental, and economic factors (Contento, 2016).

Multiple social determinants influence food choices and dietary practices. These include social norms, cultural traditions, education level, economic stability, and the availability of healthy foods within local environments (Gyawali et al., 2024).

Economic constraints and food affordability often limit access to nutritious foods, particularly in low- and middle-income settings, thereby restricting the ability of individuals to implement recommended dietary guidelines (Darmon & Drewnowski, 2008). Furthermore, environmental barriers such as limited access to healthy foods, time constraints, and convenience-driven food environments frequently hinder the adoption of healthy eating behaviors (Amore et al., 2019).

Behavioral and psychological factors also play a significant role in shaping dietary practices. Habits, taste preferences, cultural food practices, and exposure to misleading nutrition information can discourage individuals from adopting healthier diets despite being aware of their benefits (Contento, 2016). Behavioral theories such as the Theory of Planned Behavior suggest that attitudes, perceived social norms, and perceived behavioral control influence health-related actions more strongly than knowledge alone (Ajzen, 1991). Consequently, effective nutrition interventions must address these behavioral and environmental determinants in addition to providing information.

Advances in **artificial intelligence (AI), machine learning (ML), and digital health technologies** have created new opportunities to address the persistent gap between nutritional knowledge and actual dietary behavior. AI systems are capable of analyzing large volumes of health, behavioral, and environmental data to generate **personalized dietary recommendations**, predict nutritional risks, and provide real-time feedback to individuals. These capabilities allow AI-driven platforms to move beyond static dietary guidelines toward more adaptive and individualized nutrition support (Phalle & Gokhale, 2025; Li et al., 2024)

The objective of this paper is to examine how artificial intelligence can bridge the gap between knowledge and action in nutrition, particularly in addressing undernutrition in India. The paper reviews behavioral determinants of dietary practices, explores AI-driven interventions that promote behavior change, and discusses implementation considerations in the Indian context.

II. THE KNOWLEDGE-BEHAVIOR GAP IN NUTRITION

Nutrition behavior is influenced by a complex interplay of psychological, socioeconomic, and environmental factors. Although many individuals are aware of dietary recommendations, this knowledge does not necessarily translate into healthy food consumption.



This phenomenon reflects the well-documented gap between nutrition knowledge and dietary practice, where behavioral and contextual factors often override rational decision-making regarding food choices (Contento, 2016; Glanz et al., 2015).

2.1 Behavioral Determinants of Dietary Choices

Behavioral science identifies several determinants that shape food choices and dietary habits. These determinants operate at individual, household, and community levels and are particularly important in understanding dietary behaviors in diverse and culturally complex contexts such as India.

1. Habit formation:

Eating patterns are strongly influenced by habitual behaviors developed through repeated exposure to certain foods and meal routines. Habits reduce the cognitive effort required for daily food decisions, leading individuals to repeatedly select familiar foods even when healthier alternatives are known. Research in behavioral nutrition suggests that once dietary habits are established, they become automatic and resistant to change unless deliberate interventions or environmental modifications occur (Gardner et al., 2012; Verplanken & Aarts, 1999).

2. Cultural and social norms:

Food choices are deeply embedded in cultural traditions, religious practices, and family customs. Cultural norms shape what foods are considered acceptable, desirable, or healthy within a community. In India, regional cuisines, traditional cooking methods, and social expectations around meals strongly influence dietary patterns. Social influences from family members, peers, and community networks also affect food choices, reinforcing established dietary behaviors across generations (Kittler et al., 2017; Popkin et al., 2020).

3. Economic constraints:

Economic factors significantly influence dietary behavior by determining food affordability and accessibility. Households with limited income often prioritize inexpensive, calorie-dense foods over nutrient-rich options such as fruits, vegetables, and animal-source foods. In low- and middle-income settings, including many parts of India, financial constraints can limit dietary diversity and contribute to persistent undernutrition and micronutrient deficiencies (Darmon & Drewnowski, 2015; Headey & Alderman, 2019).

4. Cognitive overload:

Individuals frequently encounter complex and sometimes conflicting nutritional information from various sources, including food labels, media, and health campaigns. Processing this information requires time, literacy, and cognitive resources, which may not always be available. As a result, many individuals rely on heuristics—such as taste preferences, convenience, or marketing cues—rather than nutritional knowledge when making food choices (Miller & Cassady, 2015; Swinburn et al., 2019).

These behavioral determinants are particularly relevant in the Indian context, where dietary practices are shaped by a combination of cultural traditions, household decision-making dynamics, food availability, and socioeconomic disparities. Understanding these factors is essential for designing effective nutrition interventions and behavior-change strategies that go beyond knowledge dissemination to address the underlying drivers of food choices.

2.2 Structural Barriers in India

Undernutrition in India is not solely a result of inadequate food availability. Behavioral factors such as poor dietary diversity, suboptimal infant feeding practices, and limited nutrition awareness also contribute to the problem. Public health initiatives often focus on providing information or supplements but may fail to address behavioral motivations that influence food consumption.

Behavioral interventions delivered through digital platforms have demonstrated potential to improve nutrition outcomes at scale, particularly when combined with community engagement and social norm reinforcement. Digital tools allow continuous engagement with households and caregivers, reinforcing healthy behaviors over time. (Hindustan Times., 2024)

III. ARTIFICIAL INTELLIGENCE IN NUTRITION AND PUBLIC HEALTH

Artificial intelligence refers to computational systems capable of performing tasks that traditionally require human intelligence, including pattern recognition, prediction, and decision-making. In nutrition science, AI can process large datasets related to dietary intake, health parameters, and behavioral patterns to generate personalized insights.

AI applications in nutrition include:

- Personalized diet planning
- Automated dietary assessment
- Predictive health analytics
- Behavior change interventions (Table1)

These technologies enable precision nutrition, where dietary recommendations are tailored to an individual's biological characteristics, lifestyle, and environmental context.

Recent research highlights that AI-driven nutrition systems can analyze dietary patterns, estimate nutrient intake, and provide real-time recommendations to support healthier eating behaviors. (Hindustan times, 2024) (Table1)

Table 1.
Categories of AI Tools for Nutrition Behaviour Change

AI Tool Category	Core Technology	Behaviour Change Mechanism	Example Platforms
AI Chatbots & Virtual Coaches	Natural Language Processing (NLP), Large Language Models	Personalized counselling, goal setting, reminders	AI diet coaches, conversational nutrition assistants
Food Image Recognition Systems	Computer Vision, Deep Learning	Automatic food logging and feedback on dietary choices	Foodvisor
Personalized Recommendation Systems	Machine Learning, Recommender Algorithms	Tailored diet suggestions based on user preferences, health conditions	HealthifyMe
Wearable-integrated Nutrition AI	Multimodal sensor analytics	Links activity, glucose and eating behaviour to suggest diet changes	AI-driven precision nutrition platforms
Digital Nudging Systems	Reinforcement learning, knowledge graphs	Timely prompts to encourage healthy eating choices	Nudge-based health behaviour systems
Serious Games & Gamified Platforms	Gamification algorithms, behaviour design	Reward systems for healthy eating behaviour	Playnormous

IV. AI-DRIVEN DIETARY ASSESSMENT AND MONITORING

One of the major challenges in nutrition interventions is accurately assessing dietary intake. Traditional methods such as 24-hour recalls or food diaries rely on self-reporting and are prone to recall bias.

AI technologies can automate dietary monitoring through computer vision, sensor-based tracking, and multimodal data analysis.

4.1 Computer Vision and Food Recognition

Computer vision models can analyze images of meals to identify food items and estimate portion sizes. Many systems use deep learning algorithms to detect foods in photographs and calculate nutritional content, enabling users to receive instant feedback on dietary quality. (Bakar, L., et al., 2025). Such technologies are particularly useful in countries like India where meals often consist of multiple dishes served together, making manual dietary tracking difficult.

Research institutions in India are increasingly developing artificial intelligence (AI) systems capable of recognizing and analyzing complex traditional meals—such as Indian thalis—to estimate nutritional composition and improve dietary monitoring.

For example, researchers at the International Institute of Information Technology Hyderabad have developed AI-based computer vision systems that analyze images of thali plates containing multiple dishes (e.g., rice, dal, roti, chutney, and curd). These systems use machine learning and image segmentation techniques to identify individual food items on a plate, estimate portion sizes, and calculate nutritional values such as calories, macronutrients, and micronutrients. Such technologies address a major limitation of existing dietary tracking tools, which are typically optimized for standardized Western meals and struggle with mixed, overlapping foods common in Indian cuisine (Telengana Today., 2026).

4.2 Multimodal Nutrition Tracking

Advanced AI systems integrate data from wearable sensors (e.g., accelerometers, heart rate monitors), physiological signals (e.g., glucose levels), and contextual/environmental inputs to estimate food intake and macronutrient composition. Multimodal machine learning models can combine these heterogeneous data streams to improve dietary inference accuracy and reduce reliance on self-reported food logs (Bulling et al., 2014; Thomaz et al., 2015).

Deep learning approaches applied to wearable sensor data have demonstrated high performance in detecting eating episodes and estimating nutritional intake patterns, enabling continuous dietary monitoring in real-world settings (Min et al., 2019).

Furthermore, integration of continuous glucose monitoring (CGM) with machine learning models has shown potential for predicting postprandial metabolic responses and inferring dietary composition, supporting personalized nutrition assessment (Zeevi et al., 2015). These systems reduce participant burden, improve temporal resolution of intake data, and enable automated behavioral monitoring in free-living environments (Kyritsis et al., 2019).

V. PERSONALIZED NUTRITION AND RECOMMENDATION SYSTEMS

Personalized nutrition is one of the most promising applications of AI in addressing behavioral barriers to healthy eating. Traditional dietary guidelines often provide generalized recommendations that may not reflect individual preferences, cultural food habits, or socioeconomic conditions.

AI-based diet recommendation systems analyze individual data—including health status, dietary preferences, and lifestyle factors—to generate tailored meal plans (Figure 2).

AI-powered nutrition platforms can continuously adapt dietary recommendations based on user feedback and health data, making them more responsive to behavioral changes. (Bhatt, A., 2025).

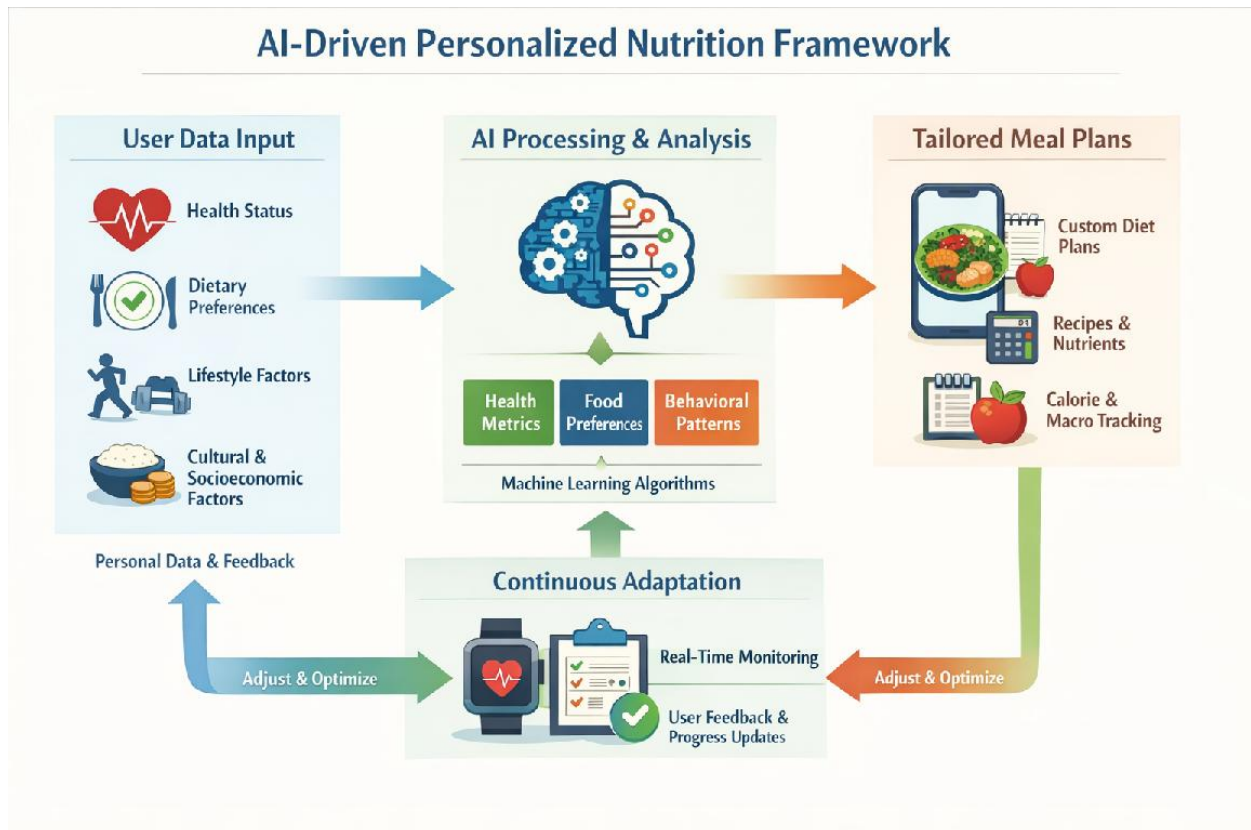


Figure 2: AI based personalized nutrition recommendations

5.1 Culturally Contextualized Recommendations

In India, personalized nutrition must consider regional cuisines, vegetarian dietary patterns, and household cooking practices.

Cultural tailoring is a critical determinant of dietary intervention effectiveness, as food choices are strongly shaped by traditions, beliefs, and local food environments (Contento, 2016).



AI systems trained on culturally relevant food databases can recommend affordable, locally available foods that meet nutritional requirements, thereby improving adherence and feasibility. Context-aware and data-driven nutrition systems enhance personalization by integrating demographic, dietary, and environmental variables (Boushey et al., 2017). Such culturally informed computational approaches can improve acceptability and long-term sustainability of dietary recommendations (World Health Organization [WHO], 2020).

5.2 Behaviorally Adaptive Recommendations

AI models can incorporate behavioral feedback loops that adjust recommendations based on user compliance. Adaptive digital interventions grounded in behavior change theory have demonstrated improved effectiveness compared to static interventions (Michie et al., 2011). For example, systems can:

- Suggest alternative foods when users repeatedly skip recommended items
- Provide reminders and motivational prompts
- Reinforce positive dietary behaviors

These mechanisms align with principles of self-regulation, reinforcement learning, and personalized feedback, which are central to sustained behavior modification (Fogg, 2009). Digital health interventions that use iterative feedback and real-time monitoring have shown improved engagement and adherence outcomes (Nahum-Shani et al., 2018). Such adaptive systems help transform passive knowledge into actionable behavior by continuously aligning recommendations with user response patterns.

VI. AI AND BEHAVIORAL CHANGE INTERVENTIONS

Artificial intelligence can influence dietary behavior through **digital behavior change strategies** grounded in behavioral science.

6.1 Nudging and Behavioral Economics

AI-powered systems can use nudging techniques to encourage healthier choices. Examples include:

- Timely reminders to consume balanced meals
- Suggestions for nutrient-rich alternatives
- Gamified reward systems for achieving dietary goals

These techniques leverage behavioral economics principles such as **choice architecture** and **positive reinforcement**.

6.2 Conversational AI and Virtual Coaching

Chatbots and virtual health assistants can provide personalized nutrition counseling at scale. Such systems can answer questions, provide recipe suggestions, and deliver tailored educational messages.

Digital health platforms that integrate AI-based coaching can improve engagement and adherence to dietary recommendations.

6.3 Community-Based Digital Platforms

Behavior change is more effective when reinforced by social networks. AI-enabled platforms can connect users with peer groups, nutrition experts, and community health workers.

Community-based approaches have historically demonstrated success in improving maternal and child nutrition by promoting peer learning and social support mechanisms. (Care Group approach., 2025; Healthify Me, 2024.)

Integrating AI with community health systems can amplify these benefits.

7. Applications in Addressing Undernutrition in India

AI technologies can be integrated into existing public health nutrition programs to address undernutrition through predictive analytics, personalized interventions, and system-level monitoring.

7.1 Early Risk Prediction

Machine learning models can analyze health records, anthropometric data, and socioeconomic indicators to identify individuals at risk of malnutrition. Predictive modeling approaches have demonstrated effectiveness in early detection of growth faltering and nutritional risk, enabling timely interventions such as supplementary feeding and targeted counseling (García-Guerra et al., 2019; World Health Organization [WHO], 2020). AI-based risk stratification tools improve the efficiency of community-level screening and resource prioritization (Rajpurkar et al., 2022).

7.2 Personalized Maternal and Child Nutrition Guidance

AI-driven mobile health platforms can deliver tailored dietary recommendations to pregnant women and caregivers, supporting optimal infant and young child feeding (IYCF) practices.



Digital decision-support systems have been shown to improve adherence to evidence-based nutrition guidance and enhance maternal engagement (WHO & UNICEF, 2021). Personalized digital interventions can address behavioral barriers by adapting recommendations based on user feedback and contextual data (Laranjo et al., 2018).

7.3 Integration with Public Health Programs

AI tools can strengthen large-scale nutrition initiatives such as:

- Integrated Child Development Services
- POSHAN Abhiyaan
- School nutrition programs

These systems can support real-time monitoring, predictive analytics, performance tracking, and improved resource allocation (Government of India, 2018; WHO, 2020). Integration of AI-enabled dashboards with public health infrastructure enhances transparency, program evaluation, and evidence-based policymaking.

VII. ETHICAL, SOCIAL, AND IMPLEMENTATION CHALLENGES

While AI offers significant potential, several challenges must be addressed for effective implementation.

8.1 Digital Divide

Limited internet access, smartphone ownership, and digital literacy may restrict the reach of AI-based interventions in rural and underserved communities (van Dijk, 2020). Unequal access to digital infrastructure can exacerbate existing health disparities and limit equitable benefits of AI-driven nutrition tools.

8.2 Data Bias and Algorithmic Fairness

AI systems rely heavily on training data. If datasets do not adequately represent diverse populations, recommendations may be inaccurate or inequitable (Obermeyer et al., 2019). Algorithmic bias can lead to systematic errors in risk prediction and may disproportionately affect marginalized groups. Ensuring representative datasets and transparent model validation is therefore essential.

8.3 Privacy and Data Security

Nutrition applications often collect sensitive health, behavioral, and biometric data. Robust data protection mechanisms, including encryption, informed consent, and secure data storage protocols, are critical to maintaining user trust and preventing misuse (Mittelstadt & Floridi, 2016). Ethical governance frameworks should guide data collection, sharing, and storage practices.

8.4 Cultural Sensitivity

AI systems must respect cultural food practices, religious dietary restrictions, and regional eating patterns to ensure user acceptance and sustained engagement (Betancourt et al., 2003). Incorporating culturally diverse food databases and context-aware recommendation algorithms enhances relevance and usability across populations.

VIII. FUTURE DIRECTIONS

Future AI-driven nutrition systems are expected to integrate **precision nutrition approaches**, incorporating genomics and microbiome data to enable highly individualized dietary recommendations (Ordovas et al., 2018; Zeevi et al., 2015). Machine learning models can leverage multi-omics data to predict metabolic responses and optimize personalized interventions (Zeevi et al., 2015).

Integration with wearable health sensors will further enhance continuous dietary and metabolic monitoring. Wearable technologies enable real-time data collection on physiological parameters, supporting adaptive nutrition guidance (Piwek et al., 2016).

The incorporation of real-time digital coaching tools, including emerging interfaces such as augmented and immersive technologies, may improve user engagement and behavioral adherence in health interventions (Topol, 2019). AI-enabled systems can dynamically adjust recommendations based on behavioral feedback and sensor-derived health indicators (Topol, 2019).

At the population level, AI can strengthen nutrition surveillance by analyzing large-scale health datasets, enabling early detection of emerging nutritional trends and supporting targeted public health responses (World Health Organization [WHO], 2021). Data-driven surveillance systems can enhance evidence-based policymaking and resource allocation.

Finally, effective implementation will require interdisciplinary collaboration among technologists, nutrition scientists, behavioral researchers, clinicians, and public health professionals to ensure ethical, equitable, and context-appropriate system design (Ordovas et al., 2018; Topol, 2019).

IX. CONCLUSION

The gap between knowledge and dietary behavior represents a major barrier to addressing undernutrition in India. Traditional nutrition education approaches often fail to influence long-term eating habits because they do not adequately address behavioral, cultural, and contextual factors.

Artificial intelligence offers powerful tools to bridge this gap by delivering personalized, data-driven, and behaviorally informed nutrition interventions. AI systems can automate dietary assessment, provide culturally relevant recommendations, and deliver real-time behavioral nudges that encourage healthier food choices.

When integrated with public health programs and community-based strategies, AI has the potential to transform nutrition interventions from static information campaigns into dynamic, adaptive systems that promote sustained behavior change.

However, successful implementation requires careful consideration of ethical, technological, and social factors, including data privacy, algorithmic fairness, and equitable access to digital technologies.

By combining technological innovation with behavioral science and public health strategies, artificial intelligence can play a pivotal role in reducing undernutrition and improving population health in India.

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