International Journal of Medical Science and Clinical Research
www.journalofmedical.com
Online-ISSN: 2664-7761
Received: 03-12-2025, Accepted: 02-01-2026, Published: 17-01-2026
Volume 8, Issue 1, 2026, Page No. 7-11

Artificial intelligence in predicting obesity risk and designing preventive nutrition therapies: A review

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Abstract
Obesity has emerged as one of the most pressing global public health challenges, driven by complex interactions among genetic, behavioural, environmental, and socioeconomic factors. Conventional approaches to obesity risk assessment and nutritional intervention often rely on population-based models that fail to account for individual variability. Recent advances in artificial intelligence (AI) and machine learning (ML) have transformed obesity research by enabling accurate prediction of obesity risk and facilitating the development of personalized, preventive nutrition therapies. This review explores the role of AI in obesity prediction, including the use of machine learning algorithms, deep learning models, and big data analytics to integrate anthropometric, dietary, lifestyle, genetic, and metabolic data. Furthermore, it highlights AI-driven approaches for designing personalized nutrition interventions, behaviour modification strategies, and digital health tools for obesity prevention. Ethical challenges, data limitations, and future research directions are also discussed. The review underscores the potential of AI-based systems to revolutionize preventive nutrition and support precision public health strategies for obesity management.

Keywords: Artificial intelligence, obesity prediction, machine learning, personalized nutrition, preventive nutrition therapy, precision health

Introduction

Obesity is a multifactorial chronic condition characterized by excessive fat accumulation that increases the risk of non-communicable diseases such as type 2 diabetes mellitus, cardiovascular diseases, hypertension, metabolic syndrome, and certain cancers (Badhwar *et al*., 2020) [9]. According to global estimates, the prevalence of overweight and obesity has risen dramatically over the past few decades (Stevens *et al*., 2012) [41], affecting both developed and developing countries. Traditional obesity prevention strategies often focus on generalized dietary guidelines and physical activity recommendations, which may not adequately address inter-individual differences in metabolism, genetics, lifestyle, and environmental exposure (Kumanyika *et al*., 2008) [21].

Artificial intelligence (AI), encompassing machine learning (ML), deep learning (DL), and data-driven modeling techniques (Jain *et al*., 2022) [16], offers novel opportunities to enhance obesity risk prediction and design targeted preventive nutrition therapies. By processing large and complex datasets, AI systems can identify hidden patterns, predict disease risk with high accuracy, and support personalized nutrition planning (Tsolakidis *et al*., 2024) [43]. The integration of AI into nutrition science represents a paradigm shift toward precision nutrition and preventive healthcare (Aleta *et al*., 2022) [2].

Overview of Artificial Intelligence and Machine Learning in Healthcare

Artificial intelligence refers to computer systems capable of performing tasks that normally require human intelligence, such as learning, reasoning, pattern recognition, and decision-making (Korteling *et al*., 2021) [18]. Machine learning, a subset of AI, involves algorithms that learn from data without explicit programming (Sarker, 2021) [38]. Common ML approaches used in healthcare include supervised learning (e.g., regression, decision trees, support vector machines), unsupervised learning (e.g., clustering, principal component analysis), and reinforcement teaching (Eckhardt *et al*., 2023) [12].

In recent years, AI has been increasingly applied in healthcare for disease prediction, diagnostics, clinical decision support, and personalized treatment planning (Rashid and Sharma, 2025) [36]. The availability of electronic health records (EHRs), wearable sensor data, dietary assessment tools, and genomic databases has accelerated the adoption of AI-based models in nutrition and metabolic health research (Mundt *et al*., 2025) [27].

AI-Based Prediction of Obesity Risk

1. Data Sources for Obesity Prediction

AI models for obesity risk prediction rely on diverse data sources, including:

1.1 Anthropometric measurements

Anthropometric indicators such as body mass index (BMI), waist circumference, waist-to-hip ratio, and body fat percentage form the foundation of AI-based obesity prediction models (An *et al*., 2022) [3]. These measurements provide direct and clinically relevant information on body composition and fat distribution, which are strongly associated with obesity-related health risks (Bennett and

Lim, 2025) [10]. AI algorithms use longitudinal and cross-sectional anthropometric data to detect early trends of excessive weight gain, central obesity, and metabolic risk. When combined with other variables, these indicators enhance model accuracy and allow stratification of individuals into different obesity risk categories (Kalhori *et al*., 2025) [17].

1.2 Dietary intake data

Dietary intake information, obtained through food frequency questionnaires, 24-hour dietary recalls, and digital food logs, plays a crucial role in AI-driven obesity prediction (Zheng *et al*., 2024) [45]. These data help quantify energy intake, macronutrient distribution, meal timing, and dietary patterns associated with weight gain (Aparicio *et al*., 2017) [4]. AI models can identify hidden relationships between specific food choices, portion sizes, and obesity risk, overcoming limitations of traditional dietary assessment methods. The integration of repeated dietary records enables personalized risk profiling and supports the development of targeted preventive nutrition strategies (Zheng *et al*., 2024) [45].

1.3 Physical activity and sedentary behavior data

Data on physical activity levels and sedentary behavior are essential for understanding energy balance in obesity prediction (Hopkins and Blundell, 2016) [14]. AI systems analyze information on exercise frequency, intensity, duration, screen time, and occupational activity to assess lifestyle-related obesity risk. Continuous monitoring through accelerometers and fitness trackers allows machine learning models to capture daily and weekly activity patterns, identify physical inactivity, and predict long-term weight gain. Such data-driven insights support personalized recommendations to increase activity and reduce sedentary behavior (Li *et al*., 2018) [25].

1.4 Socioeconomic and demographic factors

Socioeconomic status, education level, income, occupation, age, gender, and urban–rural residence significantly influences dietary choices, physical activity, and access to healthcare (Lee and Um, 2021) [21, 22]. AI models incorporate these demographic and socioeconomic variables to better account for social determinants of obesity (Scheinker *et al*., 2019) [39]. Including these factors improves the generalizability and equity of obesity risk prediction models, enabling the identification of vulnerable populations and supporting the design of culturally and contextually appropriate preventive nutrition interventions (Kumanyika, 2019) [20].

1.5 Genetic and epigenetic information

Genetic and epigenetic data provide insights into individual susceptibility to obesity and metabolic dysregulation (van Dijk *et al*., 2015) [44]. AI algorithms analyze gene variants, polygenic risk scores, and epigenetic markers to predict obesity risk beyond lifestyle factors alone. These data help explain inter-individual variability in weight gain and response to dietary interventions. When integrated with environmental and behavioral data, genetic information enhances precision nutrition approaches aimed at preventing obesity in genetically predisposed individuals (Ramos-Lopez *et al*., 2017) [35].

1.6 Biochemical and metabolic markers

Biochemical parameters such as fasting glucose, insulin, lipid profile, inflammatory markers, and hormone levels offer valuable information on metabolic health and early obesity-related dysfunction. AI models use these markers to detect subclinical metabolic changes that precede overt obesity (Awari *et al*., 2025) [7]. The inclusion of biochemical data improves predictive accuracy and allows early identification of high-risk individuals, facilitating timely nutritional and lifestyle interventions to prevent progression to obesity and associated comorbidities (Čolak and Pap, 2021) [11].

1.7 Wearable device and mobile health data

Wearable devices and mobile health applications generate real-time, high-resolution data on physical activity, sleep patterns, heart rate, and energy expenditure (Pinheiro *et al*., 2022) [31]. AI systems leverage these continuous data streams to monitor behavioral patterns, detect deviations from healthy routines, and dynamically update obesity risk predictions (Saeed *et al*., 2025) [37]. The integration of wearable and mobile data supports personalized, adaptive nutrition and lifestyle recommendations, making obesity prevention strategies more responsive and effective in real-world settings (Arshad *et al*., 2025) [5].

The integration of multimodal data enhances the predictive accuracy of AI models and allows for early identification of individuals at high risk of obesity (Lee *et al*., 2025) [23].

2. Machine Learning Models in Obesity Risk Assessment

Several machine learning algorithms have been employed to predict obesity risk. Logistic regression and decision tree models are commonly used for their interpretability, while more advanced models such as random forests, gradient boosting, and artificial neural networks offer higher predictive performance. Deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are particularly effective in handling large-scale and time-series data, such as continuous activity tracking and longitudinal dietary patterns (Lin *et al*., 2023) [26].

Studies have demonstrated that AI-based models outperform traditional statistical methods in predicting obesity risk, particularly when complex interactions among multiple variables are involved. Early prediction using AI can facilitate timely preventive interventions before the onset of obesity-related complications (An *et al*., 2022) [3].

Role of AI in Designing Preventive Nutrition Therapies

1. Personalized Nutrition and Precision Diet Planning

AI-driven nutrition systems enable the development of personalized dietary recommendations based on individual metabolic responses, genetic predisposition, lifestyle patterns, and food preferences (Ashoka *et al*., 2026) [6]. Machine learning models can analyze dietary intake data and predict postprandial glycemic or lipid responses, allowing nutrition plans to be tailored for obesity prevention and weight management (Popp *et al*., 2022; Quan *et al*., 2025) [32, 34].

Personalized nutrition therapies designed using AI can optimize macronutrient distribution, caloric intake, and micronutrient adequacy, improving adherence and long-term effectiveness compared to standardized dietary guidelines (Ashoka *et al*., 2026) [6].

2. AI in Behavior Change and Dietary Adherence

Behavioral factors play a crucial role in obesity development and prevention. AI-powered mobile applications and digital platforms use predictive analytics and reinforcement learning to support behavior modification, dietary adherence, and physical activity engagement. Chatbots, virtual coaches, and recommendation engines provide real-time feedback, motivation, and goal tracking, enhancing user engagement in preventive nutrition programs (Ekpezu *et al*., 2023) [13].

Integration of AI with Digital Health Technologies

Wearable devices, smartphone applications, and Internet of Things (IoT)-based sensors generate continuous health data that can be analyzed using AI algorithms (Awotunde *et al*., 2021) [8]. These technologies enable real-time monitoring of physical activity, sleep patterns, dietary habits, and energy expenditure (Munguia Tapia, 2008) [28]. AI-based systems can detect deviations from healthy behaviors and provide timely nutritional guidance, thereby supporting preventive strategies against obesity (Huang *et al*., 2025) [15].

Public Health Applications of AI in Obesity Prevention

At the population level, AI can be used to identify high-risk groups, predict obesity trends, and evaluate the effectiveness of nutrition interventions (Huang *et al*., 2025) [15]. AI-driven models can assist policymakers in designing targeted public health nutrition programs, optimizing resource allocation, and addressing social determinants of obesity (Perveen, 2024) [30]. The integration of AI into public health nutrition supports data-driven decision-making and precision public health approaches (Kovalchuk, 2024) [19].

Challenges and Ethical Considerations

Despite its potential, the application of AI in obesity prediction and nutrition therapy faces several challenges (Huang *et al*., 2025) [15]. Data quality, standardization, and representativeness remain major concerns, particularly in low- and middle-income countries (Lee *et al*., 2021) [22, 24]. Ethical issues related to data privacy, algorithmic bias, transparency, and informed consent must be addressed to ensure equitable and responsible use of AI technologies. Additionally, the interpretability of complex AI models is critical for their acceptance by healthcare professionals and nutritionists (Ndabarora *et al*., 2014) [29].

Table 1: Artificial Intelligence in Predicting Obesity Risk and Designing Preventive Nutrition Therapies

Author(s) & Year	Study Objective	AI / ML Technique Used	Data Source	Key Findings	Relevance to Preventive Nutrition
Seaw *et al*. (2025)	Predict obesity risk using lifestyle and dietary patterns	Machine Learning (Random Forest, SVM)	Dietary intake, physical activity, BMI	ML models accurately predicted obesity risk with higher precision than traditional statistical models	Enabled early identification of high-risk individuals for dietary intervention
Prasad *et al*. (2025) [33]	Develop personalized nutrition recommendations	Deep Learning, Neural Networks	Food intake logs, metabolic parameters	AI-generated personalized diets improved weight control outcomes	Supported individualized preventive nutrition therapy
Triantafyllidis *et al*. (2020) [42]	Predict childhood obesity	Decision Tree, Logistic Regression	Anthropometric and socioeconomic data	AI models identified key predictors such as diet quality and sedentary behavior	Helped design targeted nutrition education programs

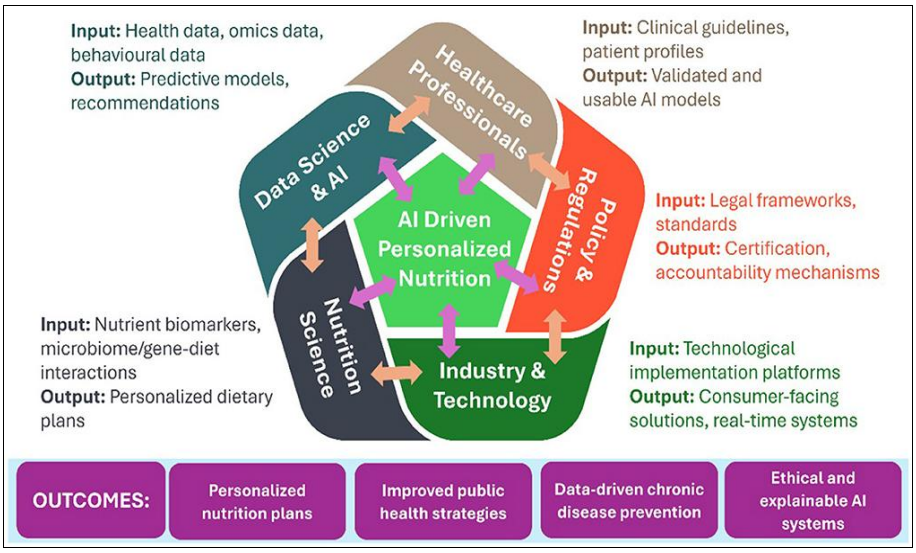

Fig 3: AI-driven precision nutrition framework for obesity prevention, showing data flow from inputs (wearables, diet logs, biomarkers) to predictive outputs and tailored dietary recommendations (Agrawal *et al*., 2025) [1]

Figure 3 illustrates a comprehensive AI-driven precision nutrition framework specifically tailored for obesity prevention. This multi-stakeholder, interdisciplinary model highlights the collaborative ecosystem required to translate raw data into actionable, personalized dietary recommendations. The pentagon-shaped diagram at the center represents five interconnected domains—Data Science & AI, Healthcare Professionals, Policy & Regulations, Industry & Technology, and Nutrition Science—with bidirectional arrows indicating continuous knowledge exchange and feedback loops (Agrawal *et al*., 2025) [1].

Conclusion

Artificial intelligence has the potential to transform obesity prevention by enabling accurate risk prediction and the design of personalized, preventive nutrition therapies. AI-based models can capture the complexity of obesity etiology and support precision nutrition approaches that go beyond traditional population-based recommendations. While challenges related to data quality, ethics, and implementation remain, the integration of AI into nutrition science offers promising opportunities to address the global obesity epidemic through targeted, efficient, and sustainable preventive strategies.

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