REVIEW ARTICLE

# Artificial Intelligence–Driven Models for Predicting Adolescent Obesity: A Comprehensive Review

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## Abstract
Childhood and adolescent obesity is an escalating global public health concern, driven by complex interactions among biological, behavioral, environmental, and social determinants. Conventional statistical approaches often fail to capture these nonlinear and high-dimensional relationships. Artificial intelligence (AI), particularly machine learning (ML), offers robust tools for early risk prediction and stratification. This review synthesizes evidence on AI- and ML-driven approaches for predicting obesity among children and adolescents. A structured literature search was conducted between February and March 2025 across PubMed, Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. Studies focusing on AI-based prediction of obesity in populations aged ≤19 years were included, while studies limited to adults or lacking methodological transparency were excluded. Evidence from 2015–2025 demonstrates that supervised ML models—especially random forests, gradient boosting, and deep learning architectures—achieve high predictive performance when applied to electronic health records, cohort data, and lifestyle datasets. However, gaps remain in model explainability, multimodal data integration, representation from low- and middle-income countries, and real-world implementation. Addressing these limitations is critical for translating AI-based obesity prediction into effective prevention and clinical decision-support systems.

## Keywords
Artificial Intelligence; Machine Learning; Predictive Modeling; Risk Stratification; Deep Learning; Childhood and Adolescent Obesity; Public Health Informatics.

## Introduction
Childhood and adolescent obesity prevalence is rising at an alarming rate worldwide posing a serious threat to the health sector because of its association with different comorbidities like cardiovascular diseases, type II diabetes, and dyslipidemia, leading to death. According to the World Health Organisation (WHO) in 2022, around 390 million children and adolescents aged 5–19 were classified as overweight, and 160 million were obese. Adolescents with obesity are more likely to become obese adults, increasing their lifelong risk of chronic diseases and premature mortality(1). Childhood and adolescent obesity have reached stressful levels globally, with a

significant rise in recent times. It was found that the prevalence of obesity among children and adolescents has been increasing since 1990, affecting worldwide(2). Obesity, involving genetic, behavioral, environmental, and socioeconomic factors, and traditional risk assessment methods, is facing difficulty in predicting obesity accurately (3).

Some of the reasons for obesity in adolescent girls are PCOS, irregular menstruation, and hormonal imbalances like raised levels of male hormones, which manifest as oligomenorrhea, hirsutism (excessive body hair), and acne, anxiety, depression, and low self-esteem (4). On the other hand, Increased Consumption of Processed Foods, Skipping Breakfast, Low Consumption of Fruits and Vegetables, reduced Physical Inactivity and Sedentary Behaviour, Lack of Physical Education in schools, and Sleep Deprivation play a significant role in the development of obesity among boys(5).

Artificial intelligence (AI) is increasingly important to address childhood and adolescent obesity, as it can analyse complex datasets, including genetic, behavioural, and environmental factors, to identify adolescents at high risk for developing obesity. Machine learning is a subcategory of artificial intelligence that analyses large-scale, advanced health data to process and identify critical obesity predictors. ML techniques can analyse non-linear relationships within datasets, describe hidden patterns, and improve predictive accuracy, making them treasured tools for obesity risk assessment and prevention strategies. AI and ML help to develop personalised interventions by predicting the most effective for specific individuals.

While there is a growing amount of literature, many reviews tend to focus on reporting the performance of individual algorithms without systematically comparing models across different datasets, data sources, and methodological contexts. In today's era of widespread electronic health records, digital health platforms, and large-scale adolescent datasets, conducting robust comparative analyses is crucial. Such analyses help inform model selection, interpret variability in performance, and evaluate translational relevance. This review fills that gap by synthesizing artificial intelligence–based models for predicting adolescent obesity, emphasising differences in algorithms, data inputs, performance ranges, and practical usefulness to support evidence-based prevention strategies and public health decisions.

## Material & Methods

This review was carried out and documented following the PRISMA guidelines, tailored for a narrative review, to improve transparency, reproducibility, and methodological rigor.

**Search strategies:**

A comprehensive and replicable literature search was conducted from February to March 2025 to find studies on artificial intelligence–based prediction of childhood and adolescent obesity. The search included databases such as PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar, chosen to encompass both biomedical and computational research. Search strategies involved an iterative process using Medical Subject Headings (MeSH) and free-text keywords. Key concepts included population ("child*" OR "adolescent*"), outcome ("obesity" OR "overweight" OR "body mass index"), and methodology ("artificial intelligence" OR "machine learning" OR "deep learning" OR "predictive model*" OR "risk prediction"). Boolean operators (AND/OR), truncation, and phrase searches optimized sensitivity and specificity. Limitations included articles published in English from January 2015 to March 2025. Additionally, the reference lists of selected studies and relevant reviews were manually screened to identify additional eligible studies.

**Inclusion and Exclusion Criteria**

Studies were included if they: (i) targeted children or adolescents (up to 19 years); (ii) utilised AI or ML methods for predicting obesity or assessing risk; and (iii) provided detailed methodology and performance results. They were excluded if they: (i) focused only on adults; (ii) covered obesity management without involving prediction; or

(iii) did not offer enough methodological clarity.

**Selection:** The sources included studies that directly addressed both theoretical and practical aspects of Artificial Intelligence in adolescent obesity, including frameworks and technological advancements, studies that focused on the prediction of childhood and adolescent obesity, studies that utilised Machine learning algorithms, and those excluded were – the ones which focused on adult obesity and its consequences, that which did not provide the required methodologies in detail. The review was done using academic articles, academic books, technical reports, online resources etc.,

**Extraction:** The initial screening of the studies was conducted independently by the authors based on titles and abstracts, followed by a full-text review of eligible articles to determine relevance and to include as much information as possible in the review article. All the authors conducted an article screening. Detailed information about each article was noted down. Extracted data included study design, population characteristics, dataset type and size, ML algorithms used, performance metrics, and key predictors.

**Synthesis:**

Given the heterogeneity of study designs and outcomes, a narrative synthesis was undertaken. Findings were organized thematically, focusing on algorithms, data sources, predictive performance, and identified risk factors.

## RESULTS

**Predictors Identified:** Across the included studies, comparative analysis revealed a core set of predictors consistently associated with adolescent obesity risk, although their relative importance varied depending on data source, population characteristics, and modeling approach. Anthropometric measures—particularly baseline body mass index (BMI), BMI trajectories, and early childhood weight gain—were the most robust and frequently ranked predictors across all algorithmic categories. Familial factors such as parental obesity and family history of metabolic disorders emerged as strong predictors, especially in tree-based and ensemble models utilizing electronic health records and cohort data. Behavioral determinants, including high-calorie dietary intake, low physical activity levels, increased screen time, and inadequate sleep duration, were commonly identified in models incorporating lifestyle and survey-based datasets. Socioeconomic indicators, such as parental education, household income, and urban residence, contributed moderate but meaningful predictive value, particularly in population-level studies. Psychosocial and environmental factors were inconsistently included across models, highlighting a critical gap and underscoring the need for future AI frameworks to integrate broader, multimodal determinants of obesity risk.

**Risk Factors for Adolescent Obesity:** Adolescent obesity is a multidimensional and difficult health issue influenced by various interrelated factors and multiple associations of individual, social, and environmental risk factors.(23)

1. **Modifiable Risk Factors** - These are significant factors in the adolescent obesity development and are categorised into various risks, such as dietary, physical activity, and other lifestyle factors. Poor eating habits, such as skipping breakfast, low consumption of vegetables, fruits and increased sugary drinks intake, have been identified as significant contributors to developing obesity. Likewise, physical inactivity, indicated by low involvement in physical education classes and excessive screen time, is linked to higher obesity prevalence. These risk factors can multiply the likelihood of developing obesity, particularly among vulnerable people (24).
2. **Non-Modifiable Risk Factors:** Non-modifiable factors are those that cannot be altered but are associated with increased obesity prevalence and contribute to obesity risk, such as genetic variations, ethnic background, and birth weight (23). Additionally, environmental factors such as exposure to air pollution and noise are emerging as serious determinants of cardiovascular health and will affect obesity outcomes among children (25).

**Table 1: Comparative Analysis of Studies with AI and ML approaches for Adolescent Obesity Prediction (2015-2025)**

| Sl No | Study (Author, Year) | ML Algorithms Used | Dataset (Size, Key Features) | Target Population/ Age | Key Performance Metrics (e.g., Accuracy, AUC, F1-score) | Key Risk Factors Identified |
|---|---|---|---|---|---|---|
| **1** | Gupta et al. (2019) (6) | Deep Learning (RNN-LSTM with attention layer), Linear Regression, Random Forest | EHR data (36,191 children, ~500 factors) | Children up to age 10, predicting within 3-year window for 2-7 years | AUC > 0.8 (prediction at 5, 11, 18 years: 0.80, 0.93, 0.92 respectively) | Previous weight/BMI, allergic urticaria, childhood obesity, morbid obesity, abnormal weight gain, high LDL/low HDL cholesterol. |
| **2** | Lee et al. (2019) (7) | Decision Tree (DT) | South Korean longitudinal cohort (~1 million children, 21 predictors) | 24-80 months | Accuracy 93% | Parental obesity(Mother obesity), SES, old pregnancy, gestational diabetes, hypertension, exclusive breastfeeding, sugar-sweetened beverages, and irregular breakfast. |
| **3** | Hammond et al. (2019) (8) | Logistic Regression, Random Forest (RF), Gradient Boosting (GB) | Multiethnic NYC cohort (>3000 children, EHR data) | Obesity at year 5 | AUC-ROC 81.7% (girls), 76.1% (boys) | Demographics, vital signs, medications, and maternal health. |
| **4** | Pang et al. (2019) (9) | Gradient Boosting Machines (GBM) / XGBoost | Pediatric Big Data (PBD) repos (~27,000 children, 102 predictors: vital signs, lab values, provider info) | Obesity in 2-7 year period using 0-2 year data | AUC-ROC 0.81 | Weight-for-height at month 24, weight at month 24, weight for height at month 18, race. |
| **5** | Kim et al. (2019) (10) | General Bayesian Network (GBN) | South Korean dataset (>11,000 students, 19 predictors) | Adolescents (three BMI categories) | Accuracy 53.7%, AUC - ROC 0.758 | Pocket money, wealth. |
| **6** | Öksüz et al. (2018) (11) | SVM (linear), kNN, DT, GB | 20 overweight/obese children | Success of 6-month weight-decrease therapy | Accuracy 85% | Heart rate, weight, age, BMI, height. |
| **7** | Zheng and Ruggiero (2017) (12) | Logistic Regression, Decision Trees (DT), k-Nearest Neighbours (kNN), Artificial Neural Networks (ANN) | >5000 high-school students | Obesity prediction | ANN (84.22% ACC, 99.46% Spec), KNN (88.82% ACC, 93.44% Spec) | Energy intake, physical activity, and sedentary behaviour. |
| **8** | Kaur and coworkers (13) | Gradient Boosting (GB), Bagging Meta-Estimator (BME), XGBoost (XGB), | UCI ML repository (2111 records, 16 attributes) | Obesity risk and meal planning | GB (98.11% accuracy) | Physical descriptions, meal calorific values, and eating habits. |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | Random Forest, SVM, KNN | | | | |
| **9** | Wang and collaborators (14) | SVMs, KNNs, Decision Trees | Genetic variations | Obesity risk | SVM (70.77% accuracy) | Genetic variations, age, sex. |
| **10** | Sulistya & Istighosah (2025) (15) | ExtraTrees, Random Forest, XGBoost, Logistic Regression, Decision Tree, Gradient Boosting, AdaBoost | Health and lifestyle data | Obesity prediction | ExtraTrees Classifier (92.6% accuracy, 92.7% precision, 92.8% recall, 92.7% F1-score) | Not specified. |
| **11** | Huang et al. (2023) (16) | Deep Neural Networks (adapted YOLOv8 model) | Short audio recordings (696 participants) | Obesity status | Global accuracy 0.70 | Vocal characteristics. |
| **12** | Awari & Kaushik (2025) (17) | LR, k-NN, SVM, Naïve Bayes, CART, RF, MLP, AdaBoost, GBM | 1100 data (21 PCA factors) | Obesity risk | Logistic Regression (97.09% accuracy) | Not specified. |
| **13** | Jeong et al. (2024) / DeepHealthNet (18) | Deep Learning (Deep HealthNet, LSTM), Naïve Bayes, RLDA, RF, DT, SVM | 321 adolescents | Adolescent obesity rates | Overall accuracy 0.8837 (boys: 0.9320, girls: 0.9163) | Height, weight, waist circumference, calorie intake, physical activity levels, gender. |
| **14** | Allen and collaborators (19) | Random Forest ML models | ABCD study data (22 sites, 120 features) | Adolescent obesity development (interaction of ecosystems) | Performance not explicitly stated | Socioeconomic/environmental factors (less educated households, low-income homes, poverty rates, single-parent households, particle pollution levels, sports activity, home values). |
| **15** | M. Abdallah et al. (2017)(20) | Bayesian Networks (BN), DecisionTrees (J48), Naïve Bayes (NB), ANN, SVM | Malaysian cohort (>4000 children) | Obesity at 12 years | J48 best | Socio-demographic, physical activity, diet. |
| **16** | Dugan et al. (2015) (21) | Random Tree, RF, J48, ID3, NB, BN | Multiethnic US cohort (>7000 children from CHICA) | Obesity at 2 years | ID3 (85% accuracy) | Overweight before 24 months, being very tall before 6 months. |
| **17** | Turer et al. (2018) (22) | Rule-based classification algorithm | Doctor visits of >7000 overweight/obese children, (EHR indices) | Paediatrician's attention to high BMI and associated medical risk | Sensitivity to BMI alone was 96%, while to BMI/Medical risk was 96.1% | Evidence from EHR indices. |

**Social Determinants of Health**: Social determinants, including socioeconomic status, family dynamics, and neighbourhood environment, significantly affect obesity rates. Children from low-income households may experience barriers to consuming healthy diets and safe environments for physical activity, further worsening the risk of developing obesity (24,25).

In India, childhood and adolescent obesity are influenced by both psychological and socio-economic factors, including emotional regulation, social environments like peer influences, Nutritional choices, and gender differences (26).

**Consequences of Obesity among children and adolescents**

**Physical Health:** Childhood and adolescent obesity have significant consequences for their physical health, including an increased prevalence of type 2 diabetes, hypertension, and dyslipidemia. Recently, obesity has been associated with the premature onset of cardiovascular diseases. Conditions like Non-alcoholic fatty liver disease and obstructive sleep apnea are high among obese children and adolescents, which is also linked with hormonal imbalances leading to complications like attaining early puberty in girls and growth plate injuries. Long-term consequences include a higher likelihood of developing adult obesity, predisposing children to chronic diseases such as coronary artery disease and certain other types of cancers(26).

**Psychological and Emotional Health:** Psychosocial well-being is significantly affected by obesity. Children often experience social stigmatisation, bullying, and isolation, which are causative of anxiety, depression, and low self-esteem. The obesity-related discrimination in children is a prevalent issue, affecting academic performance and interpersonal relationships. These psychological impacts can extend into adulthood, continuing into a cycle of emotional distress and health risks(27).

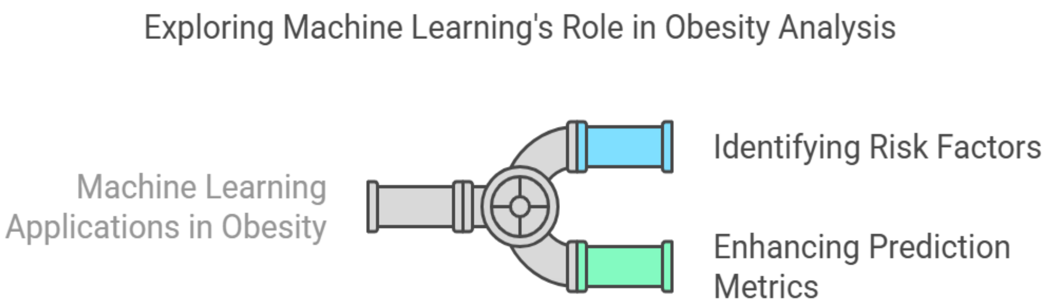
**Economic and Societal Impacts:** Childhood obesity plays a considerable role in the economic burden on healthcare systems due to the increased costs of managing comorbidities and their consequences. Families also bear financial pressures related to medical treatments and lifestyle interventions. On a societal level, obesity impacts future productivity and workforce participation. Recent global analyses predict that by 2050, the economic toll of obesity will strain healthcare systems worldwide, emphasizing the urgency of early preventive measures(28).

**The purpose of Artificial Intelligence in obesity prediction is–**

The purpose of machine learning is –

- To identify the potential risk factors contributing to obesity among Children and adolescents, by placing their patterns and ranking
- To determine the prediction to improve metrics in terms of accuracy, sensitivity, and specificity(29).

**Figure 1: Purpose of Artificial Intelligence in terms of Machine Learning applications in the prediction of Adolescent obesity**



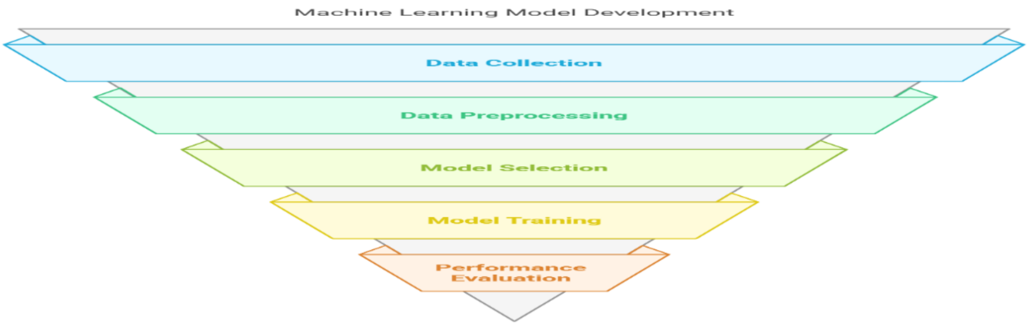
**Machine Learning Models for Adolescent Obesity Prediction**

Machine learning algorithms can be broadly classified into

- supervised - classification, regression etc.,
- unsupervised – clustering, dimensionality reduction etc.,
- reinforcement learning methods – Q learning, deep Q networks etc.,

In obesity prediction, supervised learning approaches are the most commonly used, as they rely on labeled data to train models. A wide range of ML algorithms can commonly be useful for obesity classification. These algorithms include Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), K-Nearest Neighbors (KNN), and Naive Bayes (NB). Inspired by neural networks in the human brain, an ANN can perform tasks such as classification and image recognition. Support Vector Machines (SVMs) are robust classification and regression algorithms that find a hyperplane to separate data points. Decision Trees create a tree-like structure for interpretable models and decision-making, while Naive Bayes employs Bayes' theorem for probabilistic classification. Random Forest is an ensemble of decision trees to reduce overfitting. K-Nearest Neighbours (KNN) makes predictions based on neighbouring data points, and Logistic Regression models the probabilities of binary outcomes (30).

**Figure 2: Steps of development of a Machine learning model for the prediction of obesity**




To build a machine-learning model for predicting obesity, the following steps are to be followed–

- The objectives to be clearly defined for the machine learning model to be built by considering-
- The problem to be solved (e.g., predicting obesity risk in adolescents)
- The type of machine learning algorithm that is suitable (Supervised, Unsupervised, Reinforcement Learning) as per the Hypothesis and objective.

The expected outcome (Classification, Regression, Clustering, etc.).

**Data collection:**

Gather relevant data from surveys, databases, etc., ensuring that the data is representative of the target population.

**Data Preprocessing**

- Handling Missing Data: Check for missing values and remove them.
- Feature Selection: Extract meaningful features from raw data, reduce dimensionality, and improve model performance.
- Normalization/Standardization: Scale features to ensure uniformity by encoding numerical variables into categorical variables
- Data Splitting: by splitting the data into training (70-80%), validation (10-15%), and test (10-15%) sets.

**Choose the Right Model**

- Supervised Learning: For the labelled data, Logistic Regression, Random Forest, and Neural Networks may be used.
- Unsupervised Learning: For clustering and pattern recognition, K-Means may be used.

- Deep Learning: For complex models like image-based learning, CNNs may be used.

**Train the Model**

- Fit the model to the training data.
- Use techniques like cross-validation to prevent overfitting.
- Optimise hyperparameters using Grid Search or Bayesian Optimisation.

**Evaluate Model Performance**

- Classification Metrics: Accuracy, Precision, Recall, F1-score, ROC-AUC.
- Regression Metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE).
- Overfitting Check: Compare training and validation accuracy.

**Deploy the Model**

- Convert the trained model into an API
- Deploy on cloud platforms
- Monitor real-world performance and retrain periodically.

**Continuous Improvement**

- Collect feedback and improve the model with new data.
- Fine-tune hyperparameters.
- Keep models up to date with current research (31).

**Data set types for machine learning**

The types of datasets that are used in Machine learning models to predict obesity are –

- Surveys – In-person Interviews, Telephonic interviews, mailed and online questionnaires
- Cohort studies, which may be either retrospective or prospective, and longitudinal studies
- Electronic Health records – data on patients' medical history, prescriptions, allergies, treatment data, radiology images, HMIS data, etc.
- Image datasets.

The predicted outcomes are usually of two types: categorical outcomes, where the person can be normal, overweight, or obese, and numerical outcomes, where the prediction is based on BMI and BMI percentiles(32).

**Factors influencing Machine learning in obesity among adolescents**

The factors that are considered for machine learning include –

- Individual factors – Age, gender, height, weight, Birthweight, Psychological and behavioural factors
- Familial or genetic factors – BMI of parents, socioeconomic status of family, etc
- Lifestyle factors – sleep duration, physical activity, screen time, etc.
- Environmental – eating habits and food preferences, etc(32).

## Research Gaps

Current research on Artificial Intelligence(AI) approaches towards prediction of adolescent obesity reveals several critical gaps. Existing studies predominantly utilise electronic health records, anthropometric measures, and lifestyle surveys, with limited exploration of multimodal and non-traditional data sources such as wearable sensor outputs, geospatial indicators, voice biomarkers, and social media dietary patterns. Integration of genetic, epigenetic, and psychosocial determinants remains inadequate, and poly-omic data fusion (genomics, metabolomics, microbiome) is virtually absent. Most models are static, cross-sectional, and algorithmically narrow, relying on conventional ML without leveraging advanced architectures, including Transformers, Graph Neural Networks, or generative AI (GenAI) for synthetic data augmentation and scenario simulation. Explainability is inconsistently addressed, limiting clinical trust. Geographical bias persists, with minimal representation from low- and middle-income countries. Furthermore, privacy-preserving methods such as federated learning are underused, and real-world deployment—particularly in school health programs and mobile health applications—remains scarce. Ethical oversight, bias auditing, and fairness interventions are rarely implemented in studies. Hybrid modelling approaches that combine mechanistic frameworks with ML, as well as standardised benchmarking protocols, are lacking. Hence, addressing these gaps through multimodal integration, privacy-aware architectures, interpretable AI, and GenAI-enabled simulation could significantly enhance predictive accuracy, generalizability, and clinical utility in adolescent obesity prevention.

## Practical Applications and Real-World Relevance

From a translational perspective, AI-based obesity prediction models demonstrate several potential real-world applications. In clinical practice, integration with electronic health records may enable automated early-risk alerts, facilitating timely lifestyle counseling and referral to preventive services. Within school health programs, ML-driven screening tools could support population-level surveillance and targeted interventions. Digital health applications, including mobile apps and wearable-integrated platforms, offer opportunities for continuous risk monitoring and personalized feedback. However, implementation remains limited due to challenges related to data interoperability, model explainability, ethical governance, and external validation across diverse populations. AI-driven obesity prediction models have significant potential for real-world application. In clinical settings, integration with electronic health records can enable early identification of high-risk children, prompting targeted counseling and preventive interventions. In school health programs, ML-based screening tools may support population-level risk stratification. Mobile health applications and wearable-integrated models offer opportunities for continuous monitoring and personalized feedback. However, real-world deployment remains limited, primarily due to concerns related to data privacy, interpretability, and generalizability.

## Conclusion

This review highlights the growing promise of Artificial Intelligence in predicting childhood and adolescent obesity by capturing and analysing a wide range of interrelated risk factors. Evidence suggests that AI-driven models can achieve high accuracy and support the early identification of children and adolescents at risk, offering valuable opportunities for timely preventive action and tailored interventions. However, significant challenges include ensuring methodological consistency, improving the diversity and quality of data, validating findings across diverse populations, and effectively embedding these tools within clinical and public health systems. Advancing this field will require collaborative, interdisciplinary research efforts to strengthen the evidence base and increase the practical benefits of AI for obesity prediction, prevention, and long-term management among young populations.

## Authors Contribution

All authors have contributed equally.

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Nil

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There are no conflicts of interest.

## Declaration Of Generative Ai And Ai Assisted Technologies In The Writing Process

The authors haven't used any generative AI/AI assisted technologies in the writing process.

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