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REVIEW ARTICLE

Application of artificial intelligence in the management of childhood and adolescent obesity: A comprehensive review

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ABSTRACT

Objective: Artificial intelligence (AI) is increasingly used in childhood and adolescent obesity management, including risk prediction, dietary assessment, behavioral monitoring, personalized intervention, and digital therapeutics. This narrative review aims to synthesize current evidence and critically evaluate its methodological robustness, practical relevance, ethical challenges, and future directions. **Methods:** Literature was searched in PubMed, CNKI, and Web of Science using terms related to AI, obesity, and pediatric populations. Evidence from systematic reviews, randomized controlled trials, validated prediction models, and representative digital health interventions was prioritized. The findings were synthesized using an AI-enabled prevention–monitoring–intervention closed-loop framework. **Results:** Current evidence suggests that machine learning and deep learning can support early obesity risk prediction; computer vision may improve dietary assessment; wearable devices and Internet of Things systems enable continuous behavioral monitoring; and recommendation systems, exergaming, gamification, and digital therapeutics may promote personalized behavior change. However, the evidence remains heterogeneous, with limitations including small or single-center datasets, short follow-up periods, insufficient external validation, inconsistent outcome measures, algorithmic bias, privacy concerns, and uncertain real-world applicability. **Conclusion:** AI has the potential to shift childhood obesity management from episodic and uniform care toward proactive, adaptive, and personalized support. Future research should prioritize robust validation, privacy-preserving data governance, fairness, long-term effectiveness, and human-in-the-loop implementation across family, school, community, and healthcare settings.

Keywords: artificial intelligence, childhood obesity, weight management, wearable devices, digital therapeutics

INTRODUCTION

Childhood obesity has become one of the most urgent public health challenges of the 21st century. The World Health Organization reported that, in 2016, more than 340 million children and adolescents aged 5–19 years were classified as overweight or obese worldwide, with prevalence rates continuing to rise (World Health Organization, 2025). In China, national surveys indicate a marked increase in pediatric obesity over the past four decades, marked by earlier onset and accelerated progression, with prevalence in major metropolitan areas now approaching levels seen in high-income countries (Cai *et al.,* 2017).

The health and developmental ramifications of childhood obesity are broad and multifaceted. On the physiological level, obesity increases the risk of metabolic syndrome,

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type Ⅱ diabetes, hypertension, non-alcoholic fatty liver disease, and early-onset cardiovascular pathology (Weihrauch-Blüher *et al.,* 2019). Longitudinal cohort studies have shown that elevated body mass index (BMI) trajectories during childhood independently predict higher adult cardiovascular mortality, even after adjusting for adult BMI. Additionally, obesity may impair cognitive development and academic performance through mechanisms such as disrupted sleep, higher rates of school absenteeism, and neuroinflammatory processes, thereby reinforcing intergenerational cycles of disadvantage (Caprio *et al.,* 2020).

Conventional pediatric obesity management strategies are limited in both effectiveness and scalability. Lifestyle interventions targeting diet and physical activity require sustained family involvement, yet real-world data show high initial engagement followed by progressive attrition (Leech *et al.,* 2014). Systematic reviews report dropout rates of 20–30% in traditional behavioral programs, with frequent weight regain after completion. Moreover, the absence of engaging, immediately rewarding features reduces long-term motivation, particularly among developmentally vulnerable children.

Conventional pediatric obesity management is limited by poor adherence and lack of personalization. Artificial intelligence (AI) addresses these issues by enabling systems to perform tasks such as pattern recognition, decision-making, and natural language processing (Zahlan *et al.,* 2023). Machine learning (ML) improves performance through data-driven iteration without explicit programming, while deep learning extracts hierarchical features from complex datasets (Alkhawaldeh *et al.,* 2023). These methods support pediatric obesity care by integrating genetic, clinical, behavioral, and environmental data for accurate risk prediction; enabling automated food identification and dietary monitoring via computer vision; powering conversational agents for continuous coaching; and allowing real-time activity tracking with wearables and IoT devices (Naveed *et al.,* 2025). Together, AI shifts obesity management from episodic, uniform approaches to continuous, personalized support. Fundamentally, AI offers the prospect of shifting pediatric obesity care from passive, episodic, and uniform interventions toward proactive, continuous, and personalized support systems. By automating data integration and analytical processes, AI could mitigate adherence barriers and enhance accessibility, addressing two core limitations of conventional approaches.

Therefore, this review adopts an AI-enabled prevention–monitoring–intervention closed-loop framework to synthesize current evidence on the application of artificial intelligence in childhood and adolescent obesity management (Figure 1). In this framework, AI first supports prevention by integrating clinical, behavioral, familial, and environmental data to identify children at high risk of obesity and to characterize obesity-related behaviors. It then enables continuous monitoring through wearable devices, Internet of Things systems, mobile applications, and explainable AI models that capture dynamic changes in physical activity, diet, sleep, sedentary behavior, and weight-related indicators. Based on these data streams, AI-driven recommendation systems, gamified interventions, exergaming, and digital therapeutics can provide personalized behavioral support. Importantly, intervention responses and health outcomes generate new data that can be used to update predictive models and optimize subsequent recommendations, thereby forming an adaptive learning cycle. To provide a critical overview of the current evidence base, Table 1 summarizes representative AI applications in childhood obesity management according to application domain, AI technique, study design, sample characteristics, validation strategy, main findings, limitations, and translational readiness.

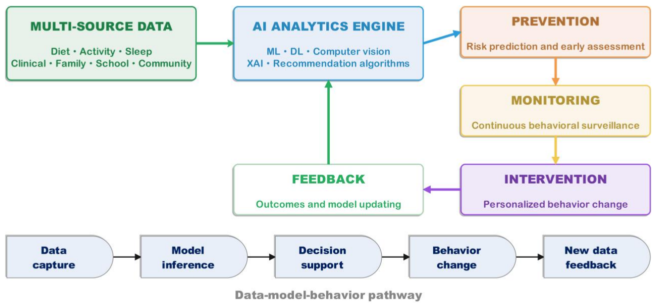

Figure 1. AI-enabled Prevention–Monitoring–Intervention Closed Loop Framework for managing childhood obesity

ARTIFICIAL INTELLIGENCE IN OBESITY RISK ASSESSMENT AND EARLY PREDICTION

Machine learning in obesity risk assessment

Traditional obesity risk identification has primarily relied on logistic regression, incorporating known predictors such as parental obesity history, birth weight, and socioeconomic status (Boakye *et al.,* 2025). Yet, childhood obesity arises from complex, nonlinear interactions among genetic predisposition, perinatal influences, family environment, lifestyle behaviors, and psychosocial factors—relationships that conventional models struggle to capture (Chatterjee *et al.,* 2020). ML, especially ensemble methods, overcomes these limitations by automatically detecting feature interactions, recognizing nonlinear patterns, and maintaining strong performance with high-dimensional data (Kaur *et al.,* 2022).

Table 1: Representative AI applications in childhood obesity management and critical appraisal

Domain	AI technique	Sample/design	Main finding	Strengths	Limitations	Translational readiness
Risk prediction	XGBoost	Large pediatric dataset + external validation	Obesity risk prediction	Large sample, interpretable model	Regional sample, generalizability unclears	Moderate
Risk prediction	Deep learning	Adolescent prediction model	88.42% accuracy	Temporal modeling	Need broader validation	Moderate
Dietary assessment	Computer vision	Dietary image analysis	Food recognition and energy estimation	Lower user burden	Portion estimation still difficult	Emerging
Monitoring	IoT + ML	362 children	Weight-change prediction	Real-time data	Limited sample and follow-up	Emerging
Recommendation	Big data + recommender system	1,727 participants	Improved weight status and behaviors	Real-world platform	Causal inference limited	Moderate
Intervention	Active video games	Meta-analysis	Reduced BMI z-score	Engaging intervention	Long-term effect unclear	Moderate

IoT, Internet of Things; ML, Machine learning; BMI, Body Mass Index.

Xue et al. compared four ML models for childhood obesity prediction using data from 19,024 children and adolescents (aged 2–18 years) in Beijing and Tangshan, with external validation in 2,410 independent participants (Xue *et al.,* 2026). Predictors included 28 variables across demographic, family, socioeconomic, lifestyle, and perinatal domains. This study shows that the ML-based XGBoost model is an effective ensemble learning method for predicting childhood obesity, aiding clinical doctors in assessing the risk of childhood obesity. Parallel investigations internationally have advanced machine learning applications for pediatric obesity prediction. Cheng et al. analyzed data from 6,614 children aged 0 to 4 years and found that five clinical encounters provided the best prediction accuracy, with a mean absolute error (MAE) of 0.98 and an R^2 value of 0.72. From a total of 269 variables, they identified 24 key predictors (Cheng *et al.,* 2022). These results demonstrate that artificial intelligence can facilitate practical early screening for obesity risk using limited clinical data, allowing for timely interventions during routine pediatric care. Another study by Jeong and colleagues developed DeepHealthNet, a deep learning framework specifically designed for adolescent obesity prediction incorporating temporal attention mechanisms to model developmental stage transitions and sequential dependencies (Jeong *et al.,* 2024). The framework achieved 88.42% accuracy in predicting adolescent obesity using anthropometric and behavioral variables.

The application of AI in the preliminary identification of overweight and obese individuals offers substantial improvements in operational efficiency while facilitating the systematic aggregation and analysis of large-scale datasets. This process generates critical evidence to inform and support data-driven public health policy development.

Artificial intelligence in Nutritional Assessment

Dietary assessment is fundamental to personalized nutrition planning, enabling self-monitoring that supports behavior change. However, conventional dietary tracking methods impose substantial cognitive and time burdens on individuals and are prone to inaccuracies due to reliance on self-reporting. These limitations highlight the need for objective, scalable solutions to quantify food intake. Recent advances in artificial intelligence offer a promising alternative through image-based food recognition. Given the widespread availability of camera-equipped smartphones, this approach can provide a practical, population-scale solution for automated dietary assessment, reducing user burden while improving accuracy.

Traditional dietary assessment methods, including 24-hour recalls and food frequency questionnaires, are time-intensive, resource-demanding, and susceptible to substantial recall bias (Shim *et al.,* 2014). Computer vision advances enable automated food recognition, portion size estimation, and nutrient calculation from images, offering objective, efficient dietary assessment alternatives. Adaptation to pediatric populations requires addressing unique characteristics of children's dietary patterns, including frequent snacking, shared meals, highly variable food forms, and smaller portion sizes (Livingstone, 2022). Current solutions include development of pediatric-specific food image datasets (e.g., KidsFood-2000) and algorithm integration of contextual information including meal timing, eating environment, and reference objects for size calibration (Min *et al.,* 2023). Ho et al. compared the effectiveness of IBDAs and Real Food Visual Estimation (RFVEs) and found no significant differences in food recognition (67% vs. 71%) and energy estimation (23% vs. 24%) between the two methods (Ho *et al.,* 2021). Khan et al. developed NutriScreener, an innovative computer vision system for malnutrition screening based on a retrieval-augmented multi-pose graph attention network (Khan *et al.,* 2025). The system integrates the Contrastive Language–Image Pre-training (CLIP) visual embeddings, category-enhanced knowledge retrieval, and context-aware modules to enable reliable malnutrition detection and anthropometric measurements from child images. Using a dataset of 2,141 children (AnthroVision) for training and testing, the system achieved a recall of 0.79 and an AUC of 0.82, with significantly lower prediction errors for height, weight, and mid-upper arm circumference compared to conventional methods. These results suggest strong potential for deployment in resource-limited settings where specialized equipment and trained personnel are scarce.

The method of obtaining dietary and nutrient intake information from images is quick and user-friendly. As food image databases and food density databases continue to expand and improve globally, the application of image-based dietary assessment (IBDA) will become more widespread. In the future, this technology could enhance dietary assessments in clinical trials by accurately quantifying nutrients such as folate, vitamin B12, and energy in population studies, which is essential for the validity of clinical trial results.

AI-DRIVEN PERSONALIZED BEHAVIORAL INTERVENTION AND MONITORING

Wearable device-based intelligent monitoring

The integration of wearable technologies with Internet of Things (IoT) infrastructures facilitates the continuous acquisition of pediatric behavioral metrics, encompassing physical activity levels, sedentary behaviors, sleep characteristics, and vital physiological signals (Alshurafa *et al.,* 2017). Lee et al. developed a self-adaptive IoT architecture organized into four functional strata—perception, networking, service, and application layers—to aggregate lifestyle log data from 362 children aged between 104 and 152 months via dedicated mobile applications (Lee *et al.,* 2025). Utilizing ensemble learning algorithms, the proposed system achieved a predictive accuracy of 0.9711 and an F1-score of 0.9725 in forecasting weight changes based on integrated lifestyle information. The results indicate that well-calibrated extrinsic incentives can function as effective behavioral catalysts during the early stages of habit acquisition; however, sustainable maintenance will require interventions that mitigate the risk of intrinsic motivation decline.

Jeong et al. proposed a personalized childhood weight management framework based on explainable artificial intelligence (XAI) (Jeong *et al.,* 2025). The system collects real-time lifestyle data via Internet of Things (IoT) devices and employs a Wasserstein Generative Adversarial Network (WGAN) to address data imbalance. For weight change prediction, a hybrid model integrating TabNet and XGBoost was developed. The study utilized six-month follow-up data from 362 elementary school students, with an external validation set of 82 individuals. The model achieved an accuracy of 98.0% on the test set and 85.2% on the external validation set. Shapley Additive Explanations (SHAP) and TabNet attention mechanism analyses identified height, step count, body weight, caloric intake, and sleep duration as the primary predictive factors. By generating synthetic data to effectively mitigate class imbalance and incorporating multi-faceted XAI techniques, the framework provides dynamic, personalized decision support for early intervention in childhood obesity, combining high predictive accuracy with strong clinical applicability.

The explainable AI-based childhood weight management framework shows promising application prospects. Through continuous algorithm optimization, data dimension expansion, and enhanced clinical validation, this research direction is expected to provide more precise and reliable intelligent decision support systems for early childhood obesity prevention and control, ultimately enabling the transition from passive treatment to active prevention.

Personalized recommendation systems

Personalized recommendation technologies, commonly used in e-commerce and entertainment, can be adapted for health behavior interventions. In managing pediatric obesity, these recommendation systems should provide tailored dietary suggestions and physical activity plans that consider individual taste preferences, interests in different activities, environmental factors, and past behaviors.

Technically, collaborative filtering recommends items by leveraging the preferences of similar users, for example, suggesting foods that children with comparable tastes disliked vegetables but accepted when prepared in a certain way. Content-based methods, by contrast, align item attributes with individual health objectives and restrictions, such as recommending calcium-rich, low-sugar options tailored to a user's specific needs. Hybrid systems combine these strategies to optimize both recommendation precision and variety. Kassari et al. evaluated the effectiveness of the "BigO e-health" system in managing childhood obesity, proposing an innovative intervention model based on the Internet of Things (IoT) and big data analytics (Kassari *et al.,* 2026). The study involved a 6-month prospective observation of 1,727 participants aged 9–18 years, utilizing smart devices to objectively collect behavioral data and deliver personalized lifestyle interventions. Following implementation, the prevalence of obesity decreased significantly by 4.2% (P = 0.014), while the proportions of overweight and normal-weight individuals increased by 10.5% and 111%, respectively. Participants also exhibited notable improvements in dietary self-perception: the proportion reporting excessive eating declined by 55.1%, and positive self-rated health evaluations rose by 24.5%. These findings demonstrate that the BigO framework provides robust technical support for childhood obesity prevention and management. Its sustained efficacy highlights strong practical resilience.

The results offer compelling empirical evidence for translating e-health technologies into pediatric chronic disease management and pave the way for precision public health intervention strategies. Future directions include reinforcement learning integration enabling dynamic recommendation adaptation based on real-time user feedback—acceptance or rejection, subsequent behavioral changes, satisfaction ratings—allowing systems to continuously optimize intervention strategies.

GAMIFICATION AND DIGITAL THERAPEUTICS INTEGRATION

Exergaming and active video games

Exergaming, also termed active video gaming, integrates physical activity into interactive game experiences, offering innovative solutions to pediatric exercise engagement challenges (Gao & Chen, 2014). Refuerzo and Resurreccion conducted a systematic review and meta-analysis examining exergaming effectiveness for pediatric obesity intervention. Following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, the analysis included nine randomized controlled trials enrolling children and adolescents under 18 years with class I-II obesity, comparing exergaming interventions (e.g., Nintendo Wii, Microsoft Kinect, dance pads, etc.) to waitlist or usual care controls.

A systematic review and meta-analysis evaluated the effectiveness of active video games (AVG) as an intervention for weight management in overweight children and adolescents (Bourke *et al.,* 2023). The findings demonstrated that, compared with control groups, AVG interventions led to a statistically significant reduction in BMI zscore (-0.09; 95%CI: -0.12 to -0.05; P < 0.0001). Although reductions in body weight (-2.66 kg; P = 0.08) and BMI (-2.29; P = 0.07) did not reach statistical significance, the results indicate a favorable trend. The analysis confirmed that AVG effectively increases physical activity energy expenditure and enhance intervention adherence through gamification.

Consequently, AVGs represent a promising adjunctive strategy for pediatric obesity management. However, larger-scale, longer-term studies are warranted to confirm sustained effects, and long-term maintenance effects and potential risks including musculoskeletal injury and excessive gaming require systematic evaluation. Collaborative efforts between game developers and researchers are recommended to design evidence-based AVG interventions that can deliver durable weight management benefits.

Gamification design and behavioral mechanisms

Beyond exergaming, gamification includes elements such as points, levels, badges, social competition, avatars, and storytelling, all designed to promote healthy behavior formation and maintenance. These features tap into both intrinsic motivators—like competence, autonomy, and relatedness—and extrinsic ones, such as rewards and recognition. Self-determination theory explains this process by highlighting how people are driven by the need to feel capable (through progressively challenging tasks), autonomous (by choosing their own path), and connected (via teamwork or social interaction). Effective gamification should therefore address all three psychological needs together.

A cluster randomized controlled trial was conducted to evaluate the effectiveness of a gamified school-based intervention in preventing childhood obesity (Peña *et al.,* 2021). The study employed a multicomponent strategy that integrated health challenges, a point-based reward system, and environmental infrastructure improvements. Findings indicated that the gamification approach significantly enhanced students' intrinsic motivation to engage in health-promoting activities. After seven months of intervention, the intervention group showed a significant reduction in BMI z-score (-0.133; 95%CI: -0.25 to -0.01) and a downward trend in BMI (-0.42 kg/m^2). The results demonstrate that incorporating gamified design into school health programs can effectively improve obesity-related indicators, offering an innovative complement to traditional health education approaches.

CHALLENGES, ETHICAL CONSIDERATIONS, AND FUTURE DIRECTIONS

Data-related challenges

The collection and utilization of pediatric health data are governed by significantly more stringent ethical and privacy protection protocols compared to adult data. Key international regulations, including the European General Data Protection Regulation (GDPR), the United States'

Children's Online Privacy Protection Act (COPPA), and China's Personal Information Protection Law (PIPL), mandate specific provisions for handling children's data. These universally require explicit parental consent, adherence to data minimization principles, and strict limitations on secondary data usage (Nutbeam, 2000).

Beyond regulatory hurdles, the acquisition of continuous, high-quality data from real-world settings presents substantial logistical and economic challenges. This frequently results in a scarcity of large-scale, robust training datasets. Consequently, the current evidence base is predominantly derived from single-center studies with modest sample sizes, which lack the multi-center, large-scale external validation necessary to ensure robust model generalizability and reliable causal inference (Vayena *et al.,* 2018).

Further methodological complication arises from the natural distribution of childhood obesity within population samples, where obese children typically constitute only 10-20% of the cohort. This class imbalance risks creating predictive models that are optimized for identifying the normal-weight majority at the expense of accurately recognizing the obese cohort. To address this, advanced techniques such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) are increasingly employed to generate synthetic samples for the minority class. However, the realism, generalizability, and potential biases introduced by these synthetic data require rigorous validation, as over-reliance may embed artificial patterns that compromise model performance in real-world clinical applications.

Balancing technology and human connection

With children's increasing engagement with digital screens for health guidance, the potential implications for parent–child communication and teacher–student interactions merit scrutiny. Users of health applications engaged in discussions about health topics with their parents less frequently than non-users, suggesting that technology may act as a partial substitute for, rather than a supplement to, interpersonal dialogue. Ideally, technology should function as an enabler rather than a replacement—positioning AI as a health coach that delivers informational support and behavioral prompts, thereby complementing, not supplanting, the emotional and relational support provided by families and healthcare providers. Future system designs should therefore prioritize features that foster, rather than diminish, interpersonal connections, such as "family sharing" functions that encourage joint participation in health-related activities.

The integration of AI will change the roles of healthcare professionals. They will shift from simply providing information ("telling patients what to do") to becoming decision support interpreters ("explaining the rationale behind AI recommendations") and emotional supporters ("offering irreplaceable human connection that AI cannot provide"). This transformation calls for an evolution in medical education, focusing on developing digitally literate professionals who can effectively collaborate with AI. At the same time, it is essential to establish clear boundaries of responsibility: when AI recommendations result in adverse outcomes, the assignment of accountability must be clarified.

Beyond current technical and ethical challenges, future AI applications in childhood and adolescent obesity management should move toward an integrated precision health ecosystem. Such an ecosystem would not rely on isolated prediction models or single digital tools, but would connect real-world data streams from family, school, community, and healthcare settings with privacy-preserving AI methods, adaptive intervention strategies, and precision public health outcomes. In this vision, federated learning, digital twins, explainable AI, causal inference, and reinforcement learning may support continuous model updating and personalized intervention optimization while reducing risks related to data sharing and algorithmic opacity. Figure 2 illustrates this future AI ecosystem and highlights the need for governance mechanisms that ensure data quality, pediatric privacy protection, algorithmic fairness, human-in-the-loop oversight, and regulatory accountability. Given the complexity of implementing AI in pediatric obesity management, Table 2 summarizes the major opportunities, context-specific risks, and future directions across data, algorithms, intervention delivery, gamification, implementation, and governance dimensions.

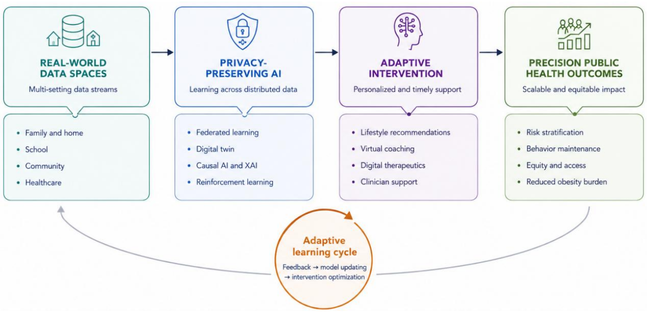

Figure 2. Future AI ecosystem for precision childhood obesity management.

CONCLUSIONS

Artificial intelligence is fundamentally transforming the paradigm of childhood and adolescent obesity management. In risk assessment, machine learning models that integrate multidimensional data demonstrate

Table 2: Key opportunities, risks, and future directions for AI-enabled childhood obesity management

Dimension	Opportunities	Context-specific risks	Future directions
Data	Continuous real-world monitoring	Pediatric privacy, consent, school-family data sharing	Federated learning, data minimization
Algorithm	Personalized prediction	Bias, class imbalance, black-box decisions	XAI, fairness auditing
Intervention	Tailored support	Low adherence, digital fatigue	Adaptive intervention, human coaching
Gamification	Higher motivation	Screen exposure, over-reliance on rewards	Evidence-based gamification
Implementation	Scalable public health support	Unequal device access, low-resource settings	Equity-oriented design
Governance	Safer clinical translation	Unclear responsibility	Regulatory framework, human-in-the-loop

XAI, Explainable Artificial Intelligence.

superior early-warning accuracy over conventional methods, with ensemble approaches such as XGBoost. In behavioral intervention, AI-driven tools, including chatbots, wearable devices, and exergaming platforms—show preliminary efficacy in promoting healthier behaviors. For personalized support, advances in explainable AI are helping to transform opaque "black box" models into interpretable and trustworthy systems capable of delivering individualized guidance.

Nevertheless, a sober assessment of current limitations remains imperative. Significant challenges persist in data privacy, algorithmic fairness, long-term efficacy, and regulatory approval, necessitating further rigorous investigation. The unique vulnerability of pediatric populations demands that AI applications undergo heightened scrutiny, ensuring that technological innovation remains aligned with the paramount objective of safeguarding child health and well-being.

Technology should serve as an enabler—not a replacement—for human-centered care. In the vision of "intelligent health," artificial intelligence ought to illuminate the path toward healthy development, complementing rather than supplanting the essential human elements of compassion and empathy. Striking a balance between technological advancement and humanistic values is crucial to fulfilling the fundamental mission of health promotion: ensuring that every child, irrespective of background, geography, or environment, has access to scientifically sound, empathetic, and sustainable support to thrive and achieve their full potential.

DECLARATION

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Author Contributions
Shitong Shao: Data collection and analysis, Methodology, Writing—Original draft. Meng Cao: Conceptualization, Reviewing and editing, Figure drawing.

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Ethical approval
Not applicable.

Informed consent
Not applicable. There are no human participants in this study, and no personal information and human images can be identified.

Conflict of interest
The authors declare no competing interest.

Use of large language models, AI and machine learning tools
During the preparation of this manuscript, the authors used Tencent Yuanbao (version 2.76.1, Tencent, China) for language polishing and improving readability. All AI-assisted revisions were reviewed and verified by the authors, who take full responsibility for the final content of the manuscript.

Data availability statement
No additional data.

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