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A Concise Review on Identifying Obesity Early: Leveraging AI and ML Targeted Advantage

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Abstract: *The pervasive nature of obesity has escalated into a global epidemic, posing a significant threat that could overwhelm healthcare systems, economies, and societal well-being. Given its strong association with debilitating chronic conditions, such as cardiovascular disease, there's an urgent need for more effective strategies to predict, prevent, and manage this complex health challenge. This review aims to explore how Artificial Intelligence (AI) and Machine Learning (ML) can be leveraged as powerful tools to enhance the early identification, proactive prevention, and improved management of obesity. Our objective is to highlight AI's potential in developing more precise and effective measures to combat this worldwide health crisis. The present review study explores the possibility of applying AI and ML in the care and prevention of pediatric obesity. The study discussed diversity of obesity causes citing genetic susceptibility, environmental driving and lifestyle preferences and emphasize the drawbacks of the customary methods of detection and treatment. The study review AI and ML models that have been used to predict the occurrence of obesity with emphasis on when the children will be very early to prevent obesity health effects. The study also reviews the implementation of AI-based trends in obesity care and compare its usage between healthcare specialists and patients. In addition, clinical practice, AI combines information in electronic health records, wearables, and health-tracking app to make person-centered treatment and evidence-based decisions possible. Furthermore, to patients, AI-based services provide them with individual coaching, motivation and long-term behavioral change due to constant monitoring and feedback. Lastly important issues such as data privacy, healthcare disparities, and social determinants of health that affect the effective implementation of AI to treat obesity, and provide suggestions on the potential research and policies to improve equity in the future.*

Keywords*: Chronic disease, prevention, personalized coaching, health management, clinical decision making, machine learning.*

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1.0 Introduction

Since 1975, global obesity rates have tripled, with projections indicating that by 2025, approximately 180 million individuals will be classified as morbidly obese, 1 billion will be obese, and 2.7 billion adults will be overweight (Huang et al., 2025; Kelly et al., 2025). Obesity is associated with an increased risk of numerous health conditions, including cardiovascular disease, various cancers, and obstructive sleep apnea ((Huang et al., 2025). In children, excess weight is also linked to adverse psychological effects, such as heightened stress levels, symptoms of depression, and reduced self-esteem (Hampl et al., 2023 and (Huang et al., 2025). These complications contribute to significantly higher healthcare costs, particularly due to the long-term management of obesity-related comorbidities. The World Health Organization estimates that by 2030, lifestyle-related conditions including those associated with obesity will be responsible for around 30% of all global deaths, emphasizing the urgent need for effective prevention and intervention strategies (Chatterjee et al., 2020).

Artificial Intelligence (AI) refers to the creation of computer systems capable of performing tasks that typically require human intelligence, such as recognizing patterns, processing language, and making decisions (Huang et al., 2025). AI is becoming increasingly integrated into healthcare, especially in the management and prevention of chronic diseases (Patricia et al., 2025). Its potential to streamline patient care, improve diagnostic accuracy, and enhance patient satisfaction through digital interfaces such as chatbots and virtual assistants has been especially apparent since the COVID-19 pandemic, which accelerated the adoption of technologies like telemedicine (Hirani et al., 2024).

Machine Learning (ML), a subset of AI, enables systems to learn and adapt by analyzing data without being explicitly programmed (Huang et al., 2025). Unlike traditional programming, ML can use either supervised learning where labeled input data guide outcomes or unsupervised learning, which identifies patterns in unlabeled data. Additionally, ML includes a method called self-supervised learning, where the system builds its own labels from data (Nnenna et al., 2025). In the healthcare domain, ML has been widely applied for disease detection and risk prediction, although its performance varies based on the chosen features, dataset quality, and algorithm design (Badillo et al., 2020).

Deep learning, a more specialized area within ML, uses multi-layered neural networks to analyze large volumes of data and has shown strong results in applications such as image and speech recognition (Gupta et al., 2021). This technique has enabled the development of advanced predictive tools in healthcare, ranging from diagnostic imaging to histological analysis and prognosis prediction [10]. Moreover, deep learning models support the analysis of various neuroimaging techniques, including PET scans, CT scans, EEGs, and newer neural network architectures like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs) (Xu et al., 2023).

CNNs have been particularly useful in analyzing structural brain data and identifying disease patterns from medical imaging such as MRI and CT scans [10]. Meanwhile, RNNs are effective for handling time-sequenced data, making them suitable for predicting obesity-related outcomes from longitudinal health datasets or mapping gene-protein networks implicated in obesity development. Additionally, speech signal data have been used alongside deep learning models to enhance the prediction of changes in neurological signals, such as EEG and MEG data (Xu et al., 2023; Huang et al., 2025).

To support the ongoing advancement of AI technologies in obesity care, continual feedback, model refinement, and robust data handling practices are essential. Figure 1 illustrates the interconnected roles and distinctions among these AI approaches.

As artificial intelligence (AI) becomes increasingly integrated into healthcare, particularly in the context of managing chronic conditions, this review explores how AI is currently being applied to assess, prevent, and treat obesity. A thorough literature review was performed using several academic databases, including PubMed, Google Scholar, Springer Link, and MDPI. The search targeted publications related to AI, machine learning, obesity (including childhood obesity), intervention strategies, overweight conditions, body mass index (BMI), personalized nutrition, behavioral guidance, and gamified health tools. This narrative review presents significant developments in the field, evaluates their clinical relevance, and examines both the potential and the limitations of adopting AI-driven methods in the fight against obesity. The study's methodology is outlined in the flow chart shown in Fig. 2.

1.1 AI/ML in health management

Artificial intelligence (AI) and machine learning (ML) have significantly transformed various areas of medicine such as dermatology, radiology, cardiology, neurology, and pharmacology by increasing the identification of patterns and the interpretation of time-based data sets (Yip et al., 2023; Varghese et al., 2024).In dermatology, AI facilitates the early identification of skin cancers using dermoscopicimage data (Huang et al., 2025). Over the last two decades, ML-assisted diagnostic tools have improved radiology by integrating imaging with genomic and pathological data, resulting in more efficient workflows and enhanced diagnostic capabilities (Najjar, 2023).

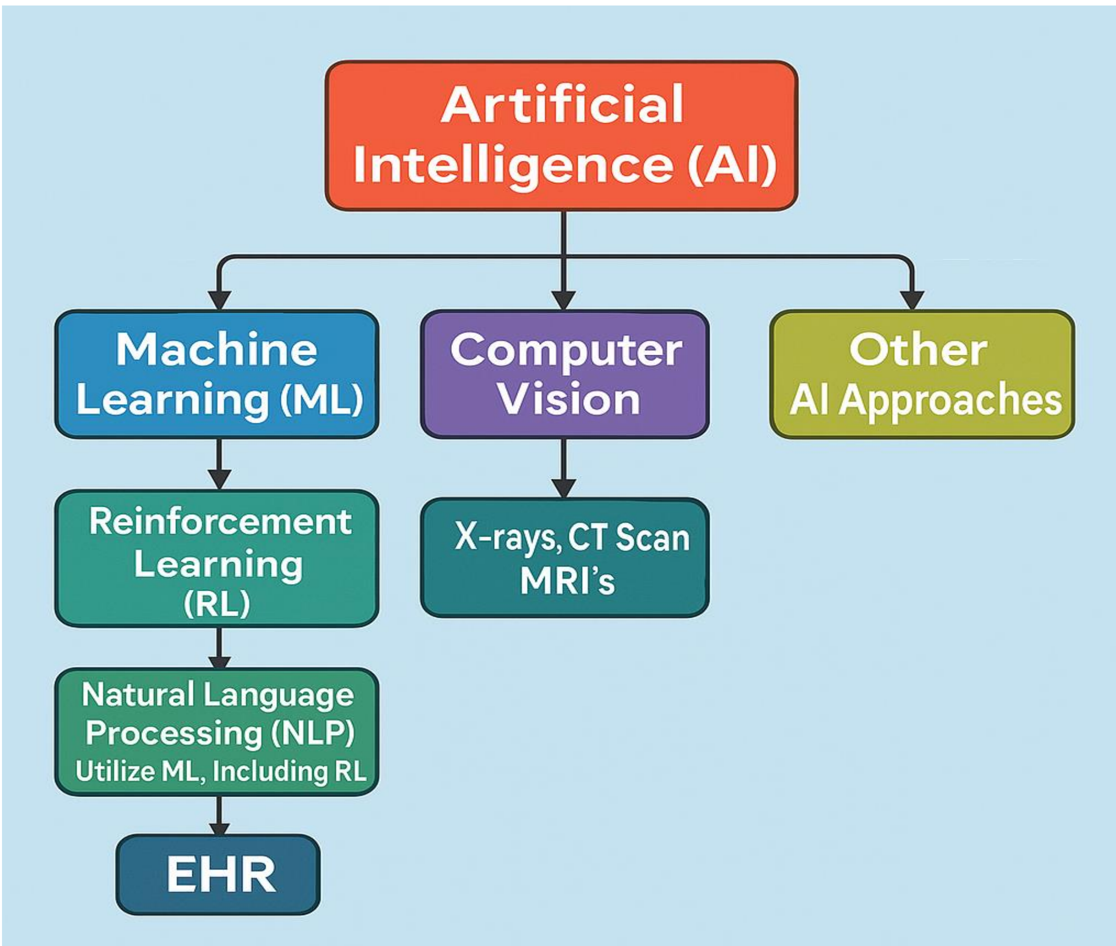

Fig.1: Overview of the hierarchical connections between Artificial Intelligence (AI), Machine Learning (ML), Reinforcement Learning, and Natural Language Processing key methodologies explored in this review for their potential applications in obesity management (Modified after Huang et al., 2025)

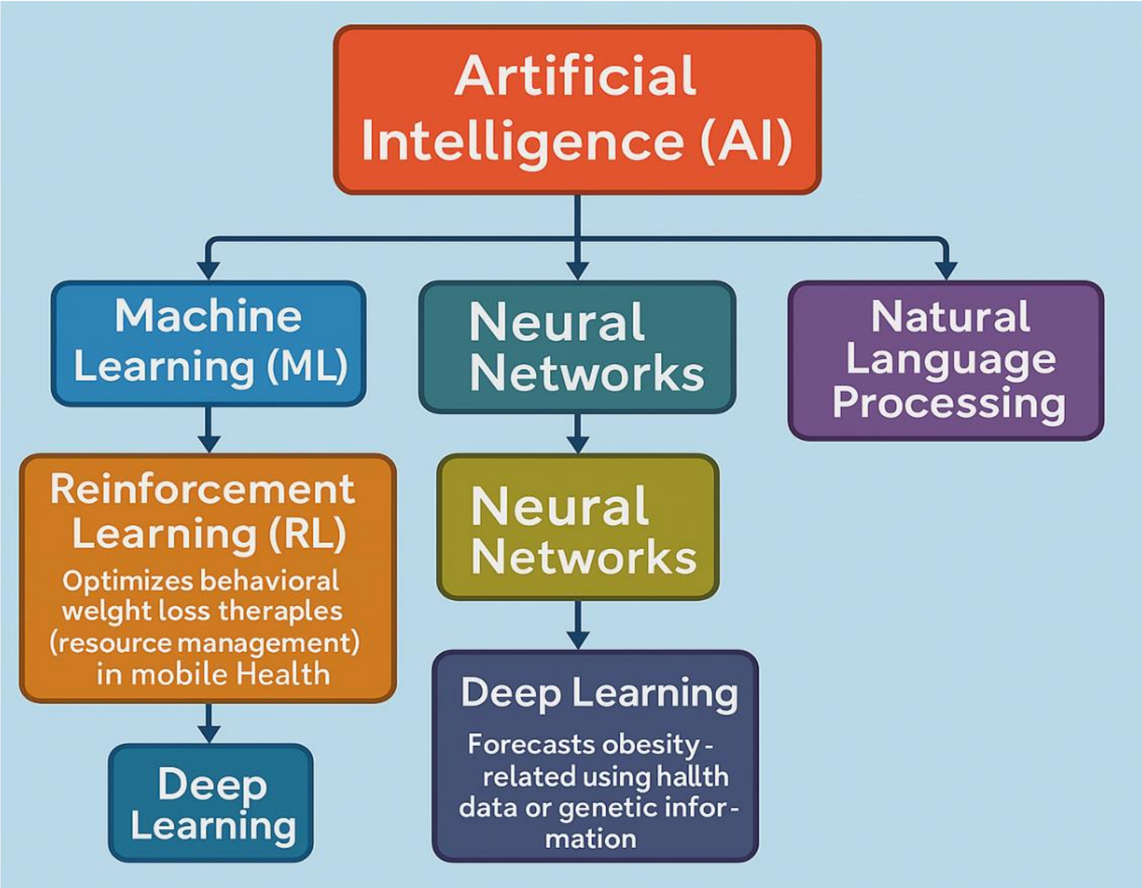

Fig. 2: Diagram illustrating various applications of artificial intelligence, machine learning, neural networks, deep learning, reinforcement learning, and natural language processing in the management of obesity (Modified after Huang et al., 2025)

Deep learning has also boosted diagnostic accuracy in breast cancer screening. A recent study using over 200,000 mammographic images showed that ML models could match radiologists in diagnostic performance (Najjar, 2023; Huang et al., 2025). Furthermore, deep learning systems interpret ECGs and echocardiograms to forecast cardiovascular phenotypes by analyzing hemodynamic features and cardiac metrics (Ghorbani et al., 2020).

1.2 AI/ML applications in obesity management

AI and ML are increasingly applied in obesity management, offering valuable insights by analyzing multifactorial health data. These technologies help identify risk factors and provide personalized care for individuals with obesity (Huang et al., 2025; Kaur et al., 2022). ML algorithms enable tailored dietary planning and optimized follow-up by modeling patterns in individual behavior and physiology (Kaur et al., 2022)). Techniques such as predictive modeling can assess obesity risk, while computer vision methods support dietary assessments and obesity surveillance (Shonkoff, 2023).

Wearables, AI-driven chatbots, and virtual assistants further enhance patient engagement and behavior monitoring (Huang et al., 2025). Advanced models like Gradient Boosting, XGBoost, and Random Forest have been particularly successful in predicting obesity risk based on lifestyle and demographic data (Ergun 2024). Synthetic data generation offers an innovative solution to data scarcity and privacy concerns by creating artificial datasets that replicate real-world trends without compromising patient confidentiality (Lee et al., 2021).

Incorporating human oversight into AI systems termed human-in-the-loop learning ensures ethical integrity and reduces algorithmic bias (Huang et al., 2025). This is especially crucial in childhood obesity, where stigma and negative self-perceptions can have long-lasting effects. AI frameworks like DeepHealthNet have demonstrated accuracy in predicting obesity by analyzing physical activity, anthropometric data, and other key indicators (Jeong et al., 2024).

1.3 AI in childhood obesity management

Childhood obesity is a growing concern, with 19.7% of U.S. children affected as of 2020 an increase from 16% in 2002 and 11% in 1994 (Jeong et al., 2024; Stierman et al., 2021). Early detection and intervention are vital, as obesity during childhood often persists into adulthood and predisposes individuals to chronic diseases. AI and ML tools can support healthier behaviors during formative years, reducing future health risks (Hedley et al., 2024; Robinson et al., 2017).

For younger populations, effective engagement strategies include gamification and interactive technologies. According to the American Academy of Pediatrics (AAP), 26 hours of structured behavioral intervention over 3–12 months can lead to measurable BMI reductions. The AAP also recommends using multicomponent strategies physical activity, nutrition, and behavior change to maximize outcomes (Hampl, 2023).

Digital interventions like virtual coaching apps and exergames a combination of gaming and physical activity meet these guidelines and improve user adherence. A meta-analysis of 23 studies found that game-based strategies enhanced nutritional knowledge, habits, and physical metrics among children (Huang et al., 2025). Similarly, a narrative review emphasized the effectiveness of exergames in improving aerobic fitness, lowering BMI, and increasing VO_2 max in overweight children (Huang et al., 2025). As these interventions develop, it is essential to adapt to children's individual preferences, cultural backgrounds, and family environments to ensure sustained impact.

2.0 Clinician perspectives on the use of AI in obesity care

Healthcare professionals play a central role in managing obesity, yet they frequently encounter difficulties in guiding patients toward lasting improvements in diet, physical activity, and behavioral change (Ernest et al., 2025). Despite ongoing efforts, obesity prevalence continues to increase (Biehl et al., 2023), indicating that traditional counseling methods may fall short in addressing the complex, long-term nature of weight management.Individuals with overweight and obesity tend to have higher rates of healthcare usage (Edwards et al., 2019), but frequent clinical visits do not always translate into effective weight loss interventions. Lifestyle change remains the most readily accessible treatment strategy; however, its success requires long-term motivation, resources, and consistency factors that many patients struggle to maintain. While medical and surgical treatments such as anti-obesity drugs and bariatric procedures are becoming more prominent (Huang et al., 2025), lifestyle interventions remain foundational. Here, AI offers new possibilities by supporting personalized, evidence-informed solutions that complement traditional care. AI systems can offer insights into individual behaviors and barriers, allowing clinicians to design targeted interventions (Oyeyemi et al., 2024). This section explores how AI can augment clinical workflows and empower providers to deliver more tailored and effective obesity care.

Table 1: AI-based approaches to childhood obesity management

Artificial Intelligence Tools	Explanations	Advantages	Representations / Cases
Future Risk Evaluation	Employs indicators (e.g., screen time, diet) to evaluate risk.	Facilitates timely support and smarter resource allocation for at-risk populations.	Personalized strategies, including social and genetic insights, help reduce childhood obesity risk.
Gamification	Gamifies healthy habits for engaging experiences.	Engaging methods motivate children to change behavior, fostering their sense of achievement and self-efficacy.	Improved fitness and weight outcomes (Huang et al., 2025).
AI-Powered Tools	Combines virtual coaching and active video games.	Integrates health with real-time monitoring of diet, physical activity, and sleep.	Apps promote activity and healthy eating (Forman et al., 2020).
Family-Focused Strategies	Engages families to foster supportive environments.	Promotes sustainable habits by considering family dynamics and preferences; encourages joint goal-setting.	Tailored strategies—supported by family and reinforced through weekly clinician messages to mothers—enhance adherence and weight management (Huang et al., 2025).
Long-Term Impacts / Results	Emphasizes enhanced quality of life and reduced healthcare costs.	Cultivates lifelong healthy habits, improves mental well-being, and lowers chronic disease risk.	AI-driven lifestyle modifications reduce chronic disease risk via EMR analytics (Colmenarejo, 2020; Huang et al., 2025) and chatbot-assisted patient coaching (Forman et al., 2020; Huang et al., 2025).

2.1 Mobile health applications and wearable monitoring devices

Mobile technologies and wearable devices such as activity monitors and smart rings are increasingly being used to tailor approaches for managing excess weight, encouraging healthier habits, and improving overall well-being (Hinchliffe et al., 2022). A comprehensive review of 12 clinical studies found that interventions delivered through smartphone applications led to small but consistent decreases in both body weight (average -1.07 kg) and body mass index (average -0.45 kg/m²) (Edwards et al., 2019), supporting their value as a useful supplement to conventional healthcare strategies.

In a multicenter randomized trial known as the Evident 3 study, participants who received a combination of a mobile app, a wearable activity monitor, and short counseling sessions alongside standard medical care experienced slight health improvements over three months, including minor reductions in weight, BMI, fat-related measurements, and waist size, as well as a notable increase in weekly low-intensity movement (32.6 more minutes per week) when compared with those who received only counseling (Huang et al., 2025). However, once the digital tools were withdrawn, these benefits tended to fade, indicating that the positive effects may be tied to the continued use of these technologies.

One possible explanation is the Hawthorne effect where individuals modify behavior when they know they are being observed (Lugones-Sanchez et al., 2022). Psychological factors also significantly influence engagement with digital tools (Kim et al., 2021). This highlights the long-term potential of wearables and mHealth apps, particularly in enabling continuous feedback loops. These systems can reduce provider burden by flagging only those patients needing immediate attention, while promoting personal accountability in users (Utomi et al., 2024). Patient attitudes toward these technologies and their behavioral impact will be further discussed in the next section.

2.2 *Evaluation on risk assessment*

AI has shown immense potential in predicting obesity risk especially childhood obesity, which often leads to chronic health conditions later in life. ML advancements have accelerated this work (Huang et al., 2025; Zhang et al., 2022), enabling the use of electronic health records (EHRs) to forecast obesity risk and identify a wide array of contributing factors, including social, demographic, and psychological determinants (Huang et al., 2025).For instance, in a study involving 327 participants aged 21 to 78 undergoing weight loss intervention, ML models were trained on up to 9 months of follow-up data. With just two weeks of input data, these models achieved prediction accuracy above 50%, increasing to 97% with eight months of data (Huang et al., 2025).

AI has also been used with public health datasets to uncover genetic, environmental, and behavioral predictors of obesity (Huang et al., 2025). Some models have refined traditional metrics, such as waist circumference (Lee et al., 2021), and explored environmental influences, such as the link between supermarket access and body weight (Zarkogianni et al., 2023).

2.3 *Refined analytical techniques*

Although body composition offers more precise health insights than BMI alone, manually analyzing imaging data (e.g., from CT or MRI scans) is time-consuming and resource-intensive (Huang et al., 2025; Hirani et al.,2024). AI-based automation can expedite this process, helping alleviate provider workload and improving diagnostic accuracy (Adetunji et al., 2022).

In obesity care, AI-enhanced imaging has been used to assess cardiovascular risk more precisely (Bays et al., 2023) and identify novel biomarkers—such as perivascular adipose tissue signatures for improved vascular function prediction (Santhanam, 2023). AI has also proven useful in surgical planning, such as improving success rates for spinal anesthesia by guiding needle placement and reducing first-attempt failure in patients with obesity (Bays et al., 2023). These advancements illustrate how AI contributes to both improved diagnostics and procedural outcomes.

2.4 *Aided clinical decision-making*

Bariatric surgery remains an important treatment for morbid obesity, yet predicting outcomes and complications remains complex (Bektas et al., 2022). A systematic review of ML in bariatric surgery highlighted applications for forecasting postoperative results, guiding treatment decisions, and enhancing patient quality of life. However, the absence of external validation in many studies raises concerns about model generalizability (Bektas et al., 2022).

Another review found ML algorithms capable of supporting decisions from pre-surgical assessment to post-operative monitoring (David & Edoise, 2025). These tools can predict risks like difficult intubation, sleep apnea, and pulmonary complications (Bellini et al., 2022). Although intraoperative applications are still emerging, AI shows promise in pharmacotherapy management and real-time optimization of surgical procedures. Moreover, predictive models are being developed to anticipate surgical success, disease remission, and long-term quality of life (Bellini et al., 2022).Despite these advances, a survey at a U.S. medical institution revealed that many physicians hesitate to initiate conversations about bariatric surgery due to gaps in knowledge, referral inefficiencies, and safety concerns (Lopez et al., 2020; Funk et al., 2016). AI-based tools such as large language models like ChatGPT-4, Bing AI, and Google Bard could assist clinicians by offering accurate, real-time information to facilitate informed discussions (Hirani et al., 2024).

In personalized nutrition, one ML study combined glucose monitoring, dietary intake, physical activity, and gut microbiota data to accurately predict post-meal blood sugar responses in 800 individuals. These results could enable providers to offer tailored dietary recommendations (Zeevi et al., 2015).On a broader scale, reinforcement learning (RL) models have been implemented to dynamically optimize behavioral weight loss (BWL) therapies. RL can match treatment intensity with individual needs and resources, maximizing effectiveness and cost-efficiency throughout the patient journey (Forman et al., 2019).

3.0 Possible Challenges/Barriers

While AI tools are promising, provider confidence and understanding remain critical barriers to implementation. In one study, a ML model predicted weight loss success at six months with 81% accuracy. However, skepticism among clinicians prompted the development of an explainability framework called PRIMO. This tool helped healthcare providers interpret the model's decisions using metrics like uncertainty visualization and personalized explanations thereby fostering trust (Varghese et al., 2024).

To ensure widespread adoption, providers must receive adequate training and support. Concerns persist regarding AI's potential to depersonalize care, along with issues of data privacy and cybersecurity. Moreover, integrating AI into existing clinical infrastructures is often challenging due to technological and organizational limitations (Varghese et al., 2024). Addressing these barriers is essential to ensure AI enhances, rather than disrupts, obesity care.

Table 2: Problems associated with AI/ML implementation in obesity care

Classification	Key Problems	Representations / Cases
Limited Representation	Incomplete datasets and underrepresentation of diverse populations, including ethnic and socioeconomic groups.	Limited inclusion of ethnicities and socioeconomic groups (Huang et al., 2025).
Data Integrity and Bias	Complex machine learning models (e.g., deep learning) lack interpretability; systems often lack explainability.	Models are difficult to interpret and audit (e.g., black-box AI systems) [51].

Privacy and Confidentiality	Risks of AI system attacks, robustness failures, and inefficiencies.	Security and confidentiality concerns in AI adoption (Khalid et al., 2023).
Workflow Integration	Difficulty incorporating AI into clinical practices and electronic health records (EHRs) due to fragmented systems and data heterogeneity.	Poor interoperability and workflow alignment (Nair et al., 2024).
Implementation Barriers	High cost of development and deployment, especially in low-resource settings.	Economic challenges in small clinics and rural areas (Khalid et al., 2023).
Provider Resistance	Concerns among healthcare professionals regarding overreliance on technology and loss of human judgment.	Hesitation from clinicians due to trust and decision-making concerns (Nair et al., 2024).
Equity in Access	Disparities in geographic and socioeconomic access to AI-powered tools.	AI benefits not evenly distributed across populations (Petersson et al., 2022).
Patient-Centric Issues	Limited patient trust, skepticism toward AI's role, and preference for human care providers.	Privacy concerns and lack of understanding about AI among patients (Zhou et al., 2023).

4.0 Patients Attitudes/ Insight Toward Ai in Managing Obesity

Artificial intelligence technologies, particularly those using reinforcement learning (RL), are revolutionizing patient-centered obesity care by enabling tailored interventions that adapt to each individual's needs. These systems analyze multiple data streams including dietary patterns, physical activity, genetic factors, and gut microbiome profiles to create highly personalized treatment plans(Huang et al., 2025).

Patients benefit significantly from AI's ability to offer continuous and affordable support through tools like virtual coaches, automated texts, and gamified apps (Taiwo et al., 2025) These platforms often operate at minimal cost and provide the same level of weight reduction as traditional methods, but with substantially reduced demands on healthcare staff. By incorporating real-time feedback and natural language interaction, AI can create engaging, accessible programs that promote sustained lifestyle changes. This approach empowers patients while simultaneously lowering healthcare costs and easing the burden on providers.

4.1 Real-time and personalized support

Behavioral weight loss (BWL) programs have proven effective, with participants typically achieving 7-10% body weight reduction (Forman et al., 2019). These interventions encourage self-monitoring, goal setting, and regular feedback from trained coaches. However, their scalability is limited by cost and availability of skilled professionals, and long-term maintenance remains a challenge less than 3% of patients sustain their weight loss post-treatment (Huang et al., 2025). Evidence shows that remote versions of BWL can achieve outcomes comparable to in-person programs, making them viable at scale (Appel et al., 2011).

AI, particularly RL-based systems, enhances the scalability and personalization of BWL by adjusting the type and intensity of support in response to real-time data (Forman et al., 2019). One pilot study examined an RL model that modified treatment based on user feedback via texts, calls, and notifications. Participants in the AI-optimized group achieved similar weight loss to those in traditional group programs about 7% while requiring just one-third of the coaching time (Huang et al., 2025). A forthcoming randomized trial will further assess a 12-month RL-guided program to determine its cost-effectiveness, weight loss outcomes, and secondary effects on physical activity, calorie consumption, and mental health indicators such as depression and binge eating (Forman et al., 2019). Unlike stepped-care models that adjust support at fixed points, RL systems continuously refine interventions, offering tailored support that aligns with patient progress. By categorizing interventions into four tiers ranging from automated messages to expert-led calls—these models deliver optimal treatment at the lowest necessary cost (Forman et al., 2019).

Natural language processing (NLP) allows AI assistants to simulate human-like conversations, improving user engagement and perceived support. Basic chatbots such as Lark offer structured interactions, but their functionality is limited. NLP-powered virtual assistants, on the other hand, can interpret free-form input and adapt responses dynamically, resulting in more personalized and effective behavioral interventions (Huang et al., 2025).

For example, the chatbot Paola was integrated into a 12-week lifestyle program called MedLiPal, which also included a wearable activity tracker, diet log, and website. Among sedentary adults aged 45-75, the program led to an average weekly physical activity increase of 109.8 minutes, a Mediterranean diet score rise of 5.7 points, weight loss of 1.3 kg, and a 2.1 cm waist reduction with high participant retention and no adverse events (Maher et al., 2020). These results are comparable to more intensive, in-person interventions and underscore the feasibility of AI-driven coaching at scale.

4.2 Targeted nutritional care

AI-powered precision nutrition goes beyond general lifestyle guidance by incorporating complex biological data such as deep phenotyping, genetics, and microbiome profiles (de Toro-Martin et al., 2017). Deep phenotyping uses in-depth clinical measures to assess individual differences in metabolic function, body composition, and physiological traits enabling a more nuanced understanding of obesity-related risks (de Toro-Martin et al., 2017). For example, studies like the Maastricht Study use tools like dual-energy X-ray absorptiometry, spirometry, and confocal microscopy to assess health outcomes beyond conventional metrics (Schram et al., 2014).

Key indicators such as visceral fat accumulation and epigenetic markers (e.g., DNA methylation) are also being explored to assess obesity risk more accurately (Ronn et al. 2015). While these approaches are resource-intensive, they enable highly personalized interventions.

Genomic data is also being used to optimize weight loss programs. A retrospective analysis of 393 participants showed that integrating single-nucleotide polymorphisms (SNPs) into ML models significantly improved weight loss predictions (Huang et al., 2025; Sinha et al., 2021). Specific SNPs, like rs17300539_G and rs2016520_C, were associated with greater weight reduction. Personalized coaching that considered these genetic traits led to meaningful weight loss in 72% of participants, with 36% losing over 5% of their body weight (Huang et al., 2025).

Similarly, microbiome-based approaches allow AI systems to tailor dietary recommendations based on an individual's gut flora. Certain bacteria, such as *Akkermansiamuciniphila* and *Alistipesobesi*, are linked to more favorable weight loss outcomes (Zeevi et al., 2015). By leveraging ML models to assess microbiota composition, clinicians can generate personalized nutrition and probiotic plans to improve metabolic health.

4.3 Long-term lifestyle interventions

AI's ability to deliver long-term support is transforming sustainable weight loss strategies. Progams like SureMediks have reported average weight loss of 14% over 24 weeks, with 99% of participants reducing body weight by at least 5% (Khokhar et al., 2024). These outcomes were achieved through gamification, goal tracking, and digital accountability features.

Applications such as the Eating Trigger–Response Inhibition Program (eTRIP) use AI to promote mindful eating via chatbot check-ins, image recognition of meals, and behavioral prompts. In a 12-week Southeast Asian trial, eTRIP reduced overeating and improved participants' mood and physical activity, with an attrition rate of just 8.4% (Lee et al., 2021). Users appreciated its personalized reminders and accessible interface, supporting its potential as a scalable digital tool.

During the COVID-19 pandemic, reduced activity contributed to rising obesity rates especially in adolescents (Wang et al., 2020). A study evaluating the AI-powered game Super Kids Adventure (SUKIA), which uses gesture recognition for real-time feedback, showed significant improvements in calorie expenditure, cardiovascular fitness, and perceived exertion in adolescents when compared to Nintendo Switch (Lee et al., 2021; Liu et al., 2022). The game's interactive and customizable design fostered regular participation and demonstrated its value as a health-promoting intervention.

Food addiction further complicates obesity treatment, often correlating with higher caloric intake, larger BMI, and relapse after weight loss (Florio, et al., 2022; Huang et al., 2025). To address this, researchers developed a machine learning–based screening tool that identified three core predictors: emotional eating, solitary eating, and consumption of comfort foods (Jeong et al., 2024). The resulting nomogram, based on the Yale Food Addiction Scale, provides a simple and effective way to incorporate food addiction screening into digital interventions.

RL-based just-in-time adaptive interventions (JITAI) dynamically tailor support based on context adjusting frequency, timing, and type of intervention as needed (Gonul et al., 2021). These systems learn from user behavior to fine-tune engagement strategies over time, with simulated studies confirming their superiority over traditional RL models in delivering timely and personalized health support (Jeong et al., 2024). Projects like POWER2DM show how such AI systems can empower patients in managing chronic conditions like diabetes while offering lessons for obesity care.

At the population level, AI enables public health officials to deploy targeted interventions. For instance, DeepHealth Net predicts obesity risk by analyzing demographic and behavioral data, improving prevention strategies (Kaur et al., 2022). AI-based meal planning tools further assist in customizing dietary guidance, ensuring sustained weight control and enhancing long-term health outcomes (Jeong et al., 2024).

5.0 Management of data privacy in weight loss coaching

The use of sensitive health data in personalized weight loss programs requires robust privacy protections. Federated learning is one such approach that trains AI models directly on user devices, ensuring personal data never leaves its origin, thereby reducing risk of exposure (Khokhar et al., 2024). This distributed method supports real-time learning while preserving privacy across diverse user bases (Khokhar et al., 2024).

To strengthen privacy further, federated learning can be combined with techniques such as differential privacy, which introduces statistical noise to protect identity, and secure multi-party computation, which allows collaborative analysis without revealing individual data (Chew et al., 2024; Huang et al., 2025). Although powerful, these hybrid methods face obstacles like high communication overhead and limited scalability, particularly when using advanced cryptographic tools such as homomorphic encryption (Azizi et al., 2010; Huang et al., 2025).

To overcome these barriers, researchers are exploring ways to enhance the efficiency of privacy-preserving techniques, making them suitable for broader deployment in healthcare. Additionally, data governance frameworks that emphasize patient ownership and informed consent are essential. These include rights like the ability to withdraw consent or request

5.1 Limitations

Despite the growing potential of wearable AI technology in obesity management, several limitations must be considered. One major barrier is the relatively low adoption of such devices among younger populations. National survey data indicate that just 30.3% of children and adolescents currently use wearable health technology, and more than half (51.6%) have never used it at all (Zhang et al., 2024). This low usage rate may limit the effectiveness of AI-driven obesity solutions for pediatric populations, as reduced access could translate into lower engagement and impact.

In addition to access, both technical and ethical challenges continue to impede the integration of AI in healthcare settings. Concerns about data privacy and digital security often deter individuals from sharing personal health information with AI systems. Furthermore, many patients express a strong preference for human healthcare providers over AI-based alternatives (Robertson et al., 2023), highlighting potential resistance to machine-augmented care models. Likewise, without appropriate policy frameworks and effective implementation strategies, healthcare professionals may hesitate to incorporate AI into routine clinical practice (Petersson et al., 2022).

Disparities in the acceptance and effectiveness of AI-based obesity interventions are also evident across racial and socioeconomic groups. For example, while Black adults experience the highest obesity rates in the U.S. at 49.9% (Stierman et al., 2017) they are also less likely than other racial groups to opt for AI-driven healthcare options (Robertson et al., 2023). This may reflect underlying social determinants of health such as income, access to technology, or systemic bias which could further exacerbate health inequities in marginalized populations (Kim et al., 2018).

Another critical limitation is the risk of bias within AI systems. Disparities can arise from non-representative training data, biased algorithmic design, or structural inequities in healthcare delivery (Hirani et al., 2024;Kim et al., 2018). To mitigate these issues, AI and machine learning models must be subjected to regular bias audits and trained on inclusive datasets that incorporate relevant social determinants. Incorporating explainable AI (XAI) frameworks can also improve system transparency and foster trust between patients and providers (Hirani et al., 2024;Colemenarejo, 2020). Additional measures, such as integrating model cards, debiasing linguistic data, and involving ethicists, community members, and social scientists in the design process, are essential to creating fair and inclusive AI systems (Mitchell et al., 2019; Huang et al., 2025).

Cultural and socioeconomic differences can also influence the utility and reception of AI in obesity care. For instance, regulatory environments vary globally some nations may restrict AI-based health solutions from receiving patents. Moreover, individuals from lower-income backgrounds may lack consistent access to internet-enabled devices or may find AI-based dietary recommendations incompatible with cultural food practices (Kim et al., 2018). Psychological barriers, including distrust of AI or a preference for human interaction, may further reduce engagement with these technologies (Kim et al., 2021).

To address these challenges, implementing within-subject longitudinal data analyses can help tailor interventions while reducing bias introduced by demographic variability (Huang et al., 2025). Privacy-related apprehensions should also be addressed through strong data governance practices, such as obtaining informed consent, anonymizing personal data, applying federated learning, and implementing data purification techniques (Khan et al., 2021).

To promote equitable access, AI-driven interventions must be designed with inclusivity in mind. This can be achieved through policy support, community-based outreach, de-identification processes, and user-centered design principles that accommodate the diverse needs of various populations.

6.0 Conclusions

The convergence of artificial intelligence and healthcare offers a transformative opportunity to reshape how obesity is prevented and managed across age groups. AI technologies hold the potential to deliver personalized, scalable, and efficient interventions that enhance diagnostic accuracy, behavioral support, and healthcare accessibility key concepts.

This review highlights the promising roles of AI in areas such as real-time coaching, precision nutrition, behavioral modification, and preventive care. While the benefits are compelling, continued efforts are needed to improve system accuracy, inclusivity, and trustworthiness. Addressing limitations related to data privacy, algorithmic bias, cultural relevance, and provider training is essential to ensure AI tools can be implemented ethically and effectively.

Successful integration of AI into obesity care will require a holistic, multidisciplinary approach. This includes robust data security measures, culturally competent clinical practices, educational initiatives for both providers and patients, and supportive policy frameworks. With sustained research, stakeholder collaboration, and community engagement, AI can serve as a valuable tool that empowers individuals and healthcare systems to deliver tailored, equitable, and cost-effective solutions for managing obesity and related metabolic conditions.

7.0 References

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