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Artificial intelligence for obesity management: A review of applications, opportunities, and challenges

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ABSTRACT

Traditional obesity management approaches, including dietary interventions, physical activity programmes, pharmacotherapy, and behavioural therapies, face significant limitations in scalability, personalisation, and long-term adherence rates. The emergence of artificial intelligence (AI) technologies, particularly machine learning and deep learning algorithms, has opened new frontiers for transforming obesity prevention, diagnosis, and management strategies. This comprehensive narrative review synthesises current evidence on AI applications in obesity management, examining technological innovations from predictive risk models to personalised digital therapeutics. The review explores AI-based diagnostic tools utilising computer vision for body composition analysis, predictive algorithms identifying high-risk individuals using electronic health records, personalised behavioural interventions powered by reinforcement learning, and remote monitoring systems integrating wearable technologies with intelligent data analytics. Furthermore, it investigates clinical effectiveness of AI-driven digital therapeutics platforms and examines AI integration within clinical decision support systems. The analysis reveals significant benefits including enhanced scalability for population-level interventions, improved personalisation through real-time data integration, increased precision in risk stratification, and potential cost-effectiveness through optimised resource allocation. However, substantial challenges remain, including data privacy and security concerns, algorithmic bias that may exacerbate health disparities, limited large-scale clinical validation, declining user engagement over time, and complex regulatory and ethical considerations. Addressing these challenges through multidisciplinary collaboration, robust validation studies, and ethical frameworks will be critical for successfully integrating AI technologies into routine obesity care and achieving equitable health outcomes across diverse populations.

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1. Introduction

The global obesity epidemic has reached unprecedented proportions, with the World Health Organization reporting that worldwide obesity rates have nearly tripled since 1975, affecting over 650 million adults and representing a fundamental threat to public health systems worldwide (World Health Organization, 2025). Obesity, clinically defined as a body mass index (BMI) of 30 kg/m^2 or higher, serves as a primary risk factor for numerous non-communicable diseases, including type 2 diabetes mellitus, cardiovascular disease, certain cancers, and obstructive sleep apnoea, whilst simultaneously contributing to reduced quality of life and increased healthcare expenditure (Hales et al., 2020; Purnell, 2000). The economic burden of obesity is substantial; in the United States, direct medical costs attributable to obesity were estimated at $173 billion in 2019 dollars, with total economic costs (including indirect costs such as productivity losses and disability payments) exceeding $260 billion annually based on 2016 data (Cawley et al., 2021).

Current approaches to obesity management encompass a multifaceted strategy involving dietary modification, increased physical activity, behavioural therapy, pharmacological interventions, and in severe cases, bariatric surgery (Burke and Wang, 2011). However, these traditional interventions face substantial limitations that impede their effectiveness and scalability. Dietary counselling and lifestyle modification programmes, whilst forming the cornerstone of obesity treatment, often suffer from poor long-term adherence rates, with studies indicating that fewer than 20 % of individuals maintain significant weight loss beyond two years (MacLean et al., 2015). The one-size-fits-all approach employed by many conventional interventions fails to account for individual differences in metabolism, genetics, psychological, cultural factors, and social determinants of health, resulting in suboptimal outcomes for many patients (Zeevi et al., 2015).

The limitations of traditional obesity management strategies have created an urgent need for innovative, scalable, and personalised approaches that can address the complex, multifactorial nature of obesity whilst maintaining cost-effectiveness and accessibility. Healthcare systems worldwide struggle to provide adequate support for the growing number of individuals requiring obesity management, with limited resources, healthcare provider shortages, and geographical barriers preventing many from accessing appropriate care. Furthermore, the chronic nature of obesity necessitates long-term monitoring and support, which places additional strain on already overburdened healthcare systems and highlights the need for automated, intelligent solutions that can provide continuous care without overwhelming human resources (Wolfenden et al., 2019).

Artificial intelligence has emerged as a transformative force in healthcare, offering unprecedented opportunities to revolutionise obesity prevention, diagnosis, and management through data-driven, personalised, and scalable interventions. AI technologies, encompassing machine learning, deep learning, natural language processing, and computer vision, possess the capability to analyse vast amounts of heterogeneous data from multiple sources, including electronic health records, wearable devices, mobile applications, and medical imaging, to generate actionable insights and personalised recommendations (Topol, 2019). The integration of AI in obesity management represents a paradigm shift from reactive, episodic care to proactive, continuous, and precision-oriented approaches that can adapt to individual needs and circumstances in real-time (Asiri et al., 2023).

Despite the growing interest and investment in AI-powered obesity management solutions, there remains a significant gap in comprehensive reviews that synthesise the current evidence, identify key challenges, and provide strategic directions for future development. The problem lies in the fragmented nature of existing research, with studies focusing on isolated applications of AI without considering the broader ecosystem of obesity management or the interconnected challenges that must be addressed for successful implementation (Azmi et al., 2025). The rationale for this review stems from the urgent need to consolidate current knowledge, identify best practices, and guide future research and development efforts in this rapidly evolving field. The novelty of this review lies in its comprehensive examination of the entire spectrum of AI applications in obesity management, from risk prediction to long-term follow-up, whilst simultaneously addressing the technical, clinical, ethical, and regulatory challenges that must be overcome. The aim of this review is to provide a thorough analysis of current AI applications in obesity management, evaluate their effectiveness and limitations, and propose strategic directions for future development. The specific objectives include: (1) systematically examining current AI applications across the obesity management continuum, (2) evaluating the clinical effectiveness and real-world performance of AI-powered interventions, (3) identifying barriers to implementation, (4) assessing ethical and regulatory considerations, and (5) proposing evidence-based recommendations for future research and development priorities.

2. Methods

This narrative review employed a comprehensive search strategy to identify and synthesise relevant literature on artificial intelligence applications in obesity management. The search was conducted across multiple electronic databases, including PubMed/MEDLINE, Embase, IEEE Xplore, ACM Digital Library, and Google Scholar, covering publications from January 2015 to December 2024. The search strategy utilised a combination of Medical Subject Headings (MeSH) terms and free-text keywords related to artificial intelligence ("artificial intelligence," "machine learning," "deep learning," "neural networks," "natural language processing," "computer vision") and obesity management ("obesity," "weight management," "bariatric," "metabolic syndrome," "body mass index," "weight loss interventions").

The inclusion criteria encompassed peer-reviewed articles, conference proceedings, systematic reviews, and meta-analyses that specifically addressed the application of AI technologies in obesity prevention, diagnosis, treatment, or management. Studies were included if they involved human subjects, presented original research findings or comprehensive reviews, and were published in English. Exclusion criteria included case reports with less than 10 participants, opinion pieces without substantial evidence synthesis, studies focused solely on general healthcare AI without specific obesity applications, and publications without clear methodological descriptions.

The literature selection process involved initial screening of titles and abstracts by two independent reviewers, followed by full-text review of potentially relevant articles. Data extraction focused on study characteristics, AI methodologies employed, clinical outcomes, implementation challenges, and key findings. Given the interdisciplinary nature of the field, additional sources were identified through reference list screening and consultation with domain experts in digital health and obesity medicine.

The narrative synthesis approach was chosen to accommodate the heterogeneous nature of the available evidence, which includes diverse study designs, AI methodologies, and outcome measures that preclude formal meta-analysis. The synthesis was structured around key thematic areas identified through iterative review of the literature, with emphasis on both technical innovations and clinical applications. Quality assessment of individual studies was conducted using appropriate tools based on study design, including the Newcastle-Ottawa Scale for observational studies and the Cochrane Risk of Bias tool for randomised controlled trials, where applicable.

3. AI applications in obesity management

3.1. Risk prediction and early detection

Artificial intelligence has demonstrated remarkable potential in identifying individuals at risk of developing obesity before clinical manifestation occurs, enabling proactive interventions that can prevent or delay obesity onset. Machine learning algorithms, particularly supervised learning approaches such as logistic regression, random forests, and gradient boosting machines, have been successfully employed to analyse longitudinal data from electronic health records, identifying patterns and risk factors that may not be apparent through traditional statistical methods (Maria et al., 2023). These predictive models incorporate diverse data sources, including demographic information, medical history, laboratory values, medication records, and social determinants of health, to generate personalised risk scores that can guide clinical decision-making and resource allocation (Markham S., 2025).

One particularly promising application involves the use of AI models to predict childhood obesity risk based on early-life factors, leveraging data from birth records, paediatric growth charts, and family history to identify high-risk children who may benefit from early intervention programmes. Studies have demonstrated that ensemble methods combining multiple machine learning algorithms can achieve prediction accuracies exceeding 85 % for identifying children who will develop obesity by adolescence, significantly outperforming traditional risk assessment tools (Pang et al., 2021). These models have incorporated novel risk factors, such as sleep patterns, screen time exposure, and neighbourhood characteristics, that were previously difficult to quantify and integrate into clinical risk assessment.

Natural language processing techniques have revolutionised the extraction of obesity-related information from unstructured clinical documentation, enabling the identification of risk factors and clinical indicators that may be buried within physician notes, discharge summaries, and patient communications (Shoenbill et al., 2019). Advanced NLP algorithms, including transformer-based models such as BERT and GPT variants specifically fine-tuned for medical text, can identify mentions of weight-related concerns, dietary patterns, physical activity levels, and psychosocial factors with high accuracy and precision (Cho et al., 2024). This capability has proven particularly valuable in large healthcare systems where manual chart review would be prohibitively time-consuming and resource-intensive.

The integration of wearable device data with predictive algorithms has opened new possibilities for continuous risk monitoring and early detection of weight gain patterns. Machine learning models trained on data from fitness trackers, smartwatches, and smartphone sensors can detect subtle changes in activity patterns, sleep quality, and eating behaviours that precede weight gain, enabling timely interventions before significant obesity develops (Adenekan, 2025). These systems can also identify environmental and behavioural triggers associated with increased obesity risk, such as changes in work schedules, seasonal variations, or major life events.

Table 1 presents a comprehensive overview of AI-based risk prediction systems currently employed in obesity management, highlighting their diverse methodological approaches, data sources, and performance characteristics.

The current evidence base for AI risk prediction in obesity management consists predominantly of retrospective cohort studies and cross-sectional analyses, with limited prospective validation studies. Most studies (approximately 70 % of reviewed literature)

Table 1
AI-based risk prediction systems for obesity management.

System/Study	AI Method	Data Sources	Population	Key Outcomes	Accuracy/Performance
Habib et al. (2022)	Random Forest + XGBoost	Publicly available clinical dataset	Adults (n = 11,000)	Obesity status prediction	AUC: 0.94, Sensitivity: 96 %
Wang et al. (2025)	Ensemble Methods	Birth data, Parental BMI, Diet and demographics	Children (n = 18,503)	Obesity Classification	Accuracy: 85 %, Specificity: 80 %
Houssein et al. (2023)	BERT-based NLP	Clinical notes, Discharge summaries	Mixed (n = 1237)	Risk factor extraction	F1-score: 0.91, Precision: 88 %
Degbey et al. (2024)	LSTM + HYBRID CNN	Wearable data, Mobile sensors	Young adults (n = 173)	Obesity Classification via gait	Accuracy: 97 %, Sensitivity: 96.3 %
Torres-Martos et al. (2024)	Deep Neural Networks	Multi-omics, Clinical features	Adults (n = 90)	Pediatric obesity	AUC: 0.92, Sensitivity: 85 %
Jeon et al. (2022)	Support Vector Machines	Biomarkers and demographic data	Adults (n = 21,100)	To predict adult obesity	Accuracy: 70 %, Recall: 77 %

demonstrate moderate-to-high certainty for technical performance metrics (AUC 0.70–0.94) in their development cohorts. However, external validation across diverse healthcare settings and populations remains limited, with fewer than 30 % of published models undergoing independent validation. Key generalisability concerns include overrepresentation of specific ethnic groups (primarily Caucasian and Asian populations), geographic concentration in high-income countries, and reliance on data from academic medical centres that may not reflect community practice patterns. Critical gaps limiting clinical adoption include: (a) absence of implementation studies demonstrating clinical utility and impact on patient outcomes, (b) lack of prospective trials comparing AI-guided interventions versus standard care, (c) insufficient evaluation of model performance degradation over time, and (d) limited assessment of cost-effectiveness and workflow integration in real-world clinical settings.

3.2. Diagnostic support and body composition analysis

The application of computer vision and deep learning techniques to medical imaging has transformed body composition assessment, providing more precise and clinically relevant measurements than traditional anthropometric indicators such as body mass

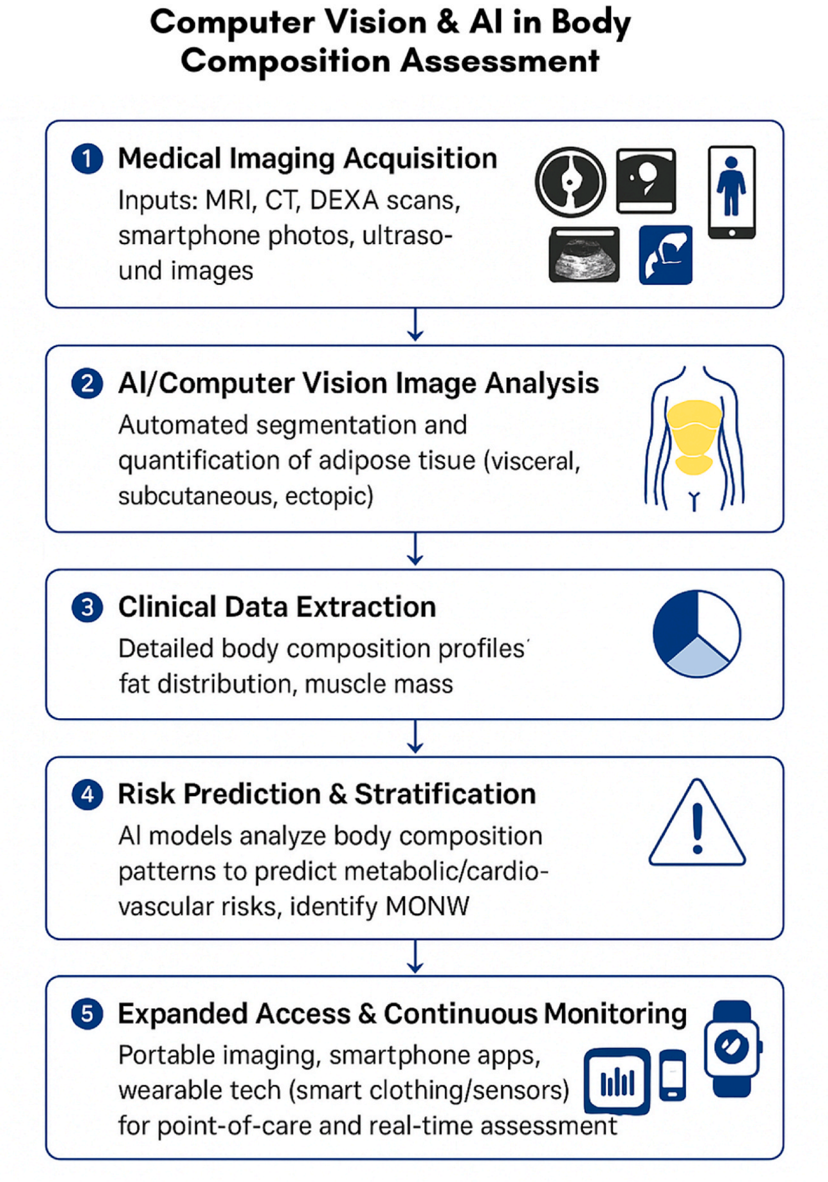

Fig. 1. Overview of the workflow for AI and computer vision-enabled body composition analysis. Steps include acquisition of medical and consumer-grade images, automated tissue segmentation and quantification, extraction of clinically relevant metrics, risk stratification through predictive modeling, expanded access via portable and wearable technologies, and delivery of personalised interventions.

index (Mohammedkhan et al., 2025). Convolutional neural networks trained on magnetic resonance imaging (MRI), computed tomography (CT), and dual-energy X-ray absorptiometry (DEXA) scans can automatically segment and quantify different adipose tissue compartments, including visceral adipose tissue, subcutaneous adipose tissue, and ectopic fat deposits in organs such as the liver and pancreas (Jeong et al., 2024). These AI-powered analysis tools provide detailed body composition profiles that are more strongly associated with metabolic risk than BMI alone, enabling more precise risk stratification and treatment planning.

Advanced image analysis algorithms have demonstrated the capability to identify subtle patterns in fat distribution that may indicate increased cardiometabolic risk, even in individuals with normal BMI but high visceral adiposity, a condition known as metabolically obese normal weight (MONW) (Blüher, 2020). Machine learning models trained on large imaging datasets can predict metabolic syndrome components, insulin resistance, and cardiovascular risk factors based solely on body composition patterns derived from medical images (Li et al., 2024). This capability has significant implications for population screening programmes, as it could identify high-risk individuals who might otherwise be missed by conventional BMI-based assessments.

The integration of AI with portable and accessible imaging technologies has expanded the potential for widespread body composition assessment beyond traditional clinical settings. Smartphone-based applications utilising computer vision algorithms can estimate body fat percentage and muscle mass from standard photographs, though with lower precision than medical imaging modalities. More sophisticated portable technologies, such as handheld ultrasound devices enhanced with AI image analysis, can provide point-of-care body composition assessment in primary care settings, community health centres, and remote locations where access to advanced imaging is limited (Kim et al., 2024).

Wearable technologies enhanced with AI capabilities have emerged as powerful tools for continuous monitoring of metabolic parameters and eating behaviours, providing real-time insights into factors contributing to obesity development and progression. Smart clothing embedded with sensors can monitor posture, movement patterns, and physiological parameters, whilst AI algorithms analyse this data to provide feedback on activity levels, caloric expenditure, and metabolic health indicators. Advanced wearable devices can even detect eating episodes and estimate food intake through analysis of jaw movement, swallowing patterns, and hand-to-mouth gestures, providing objective measures of dietary adherence that were previously impossible to obtain in free-living conditions (Zhou et al., 2025). As illustrated in Fig. 1, the workflow of computer vision and AI in body composition assessment begins with medical image acquisition, follows with automated tissue analysis, incorporates clinical risk prediction, broadens accessibility through portable and wearable technology, and culminates in personalised feedback for intervention. This visual summary clarifies the sequential integration of these steps and highlights their contribution to advanced metabolic risk assessment and clinical decision-making.

The evidence for AI-based body composition analysis is primarily derived from retrospective studies utilising existing medical imaging databases, with moderate-to-high certainty for technical accuracy when compared against gold-standard manual segmentation or reference methods. Typical study designs include algorithm development and validation studies, with emerging prospective studies and randomized trials evaluating clinical impact. Generalisability is constrained by: (a) imaging protocol variability across institutions, (b) limited representation of extreme body compositions (very high or very low BMI), (c) racial and ethnic diversity gaps in training datasets, and (d) unclear performance in common clinical scenarios (e.g., ascites, previous surgery). Key adoption barriers include: (a) regulatory uncertainty for consumer-grade body composition apps lacking FDA clearance, (b) integration challenges with existing radiology workflows and picture archiving systems, (c) limited evidence demonstrating that AI-enhanced body composition assessment improves clinical outcomes beyond standard measurements, and (d) cost-effectiveness data for implementing AI analysis in routine clinical practice.

3.3. Personalised interventions and behavioural coaching

The development of personalised obesity interventions represents one of the most promising applications of artificial intelligence in healthcare, addressing the fundamental limitation of one-size-fits-all approaches that have characterised traditional weight management programmes. Machine learning algorithms can analyse individual characteristics, preferences, behaviours, and physiological responses to create highly customised intervention plans that adapt dynamically based on user feedback and progress monitoring. These personalisation engines consider multiple factors simultaneously, including genetic predispositions, microbiome composition, metabolic rate, food preferences, cultural background, socioeconomic status, and psychological factors, to generate recommendations that are both effective and sustainable for each individual (Tsolakidis et al., 2024).

Reinforcement learning (RL) algorithms have shown particular promise in optimising intervention strategies over time, learning from user interactions and outcomes to continuously refine and improve recommendations; however, most RL-based obesity interventions remain in experimental prototype stages rather than deployed clinical products (Lauffenburger et al., 2024). Published RL applications in behavioural health have primarily focused on medication adherence and mental health interventions, with obesity-specific RL systems undergoing feasibility testing in controlled research settings. These experimental systems can identify which types of motivational messages, goal-setting strategies, and behavioural techniques are most effective for different user profiles, personalising not only the content of interventions but also their timing, frequency, and delivery methods. For example, some users may respond better to achievement-based rewards and competitive elements, whilst others may be more motivated by social support and collaborative approaches in pilot studies.

AI-powered chatbots and virtual coaches have emerged as scalable solutions for providing continuous behavioural support and motivation, with a critical distinction between research prototypes and commercially deployed products that have undergone safety validation. Deployed conversational agents for obesity management typically incorporate rule-based safety guardrails to prevent harmful advice (e.g., extreme caloric restriction, inappropriate exercise recommendations for individuals with contraindications), escalation pathways to human clinicians when concerning content is detected (e.g., eating disorder symptoms, expressions of self-harm), and content filtering to ensure cultural appropriateness and evidence-based recommendations (Aggarwal et al., 2023). These systems utilise natural language processing and dialogue management techniques to conduct meaningful conversations with users, providing personalised advice, emotional support, and motivation based on cognitive behavioural therapy principles and motivational interviewing techniques. Advanced chatbots in clinical deployment settings undergo rigorous testing for safety, including adversarial testing to identify potential harmful outputs and continuous monitoring of user-reported adverse events. Advanced chatbots can recognise emotional states from text input, adjust their communication style accordingly, and provide appropriate interventions for different psychological states and challenges within pre-defined safety boundaries. This cyclical model in Fig. 2 captures the interactive and evolving process of AI-enabled personalised obesity management, emphasizing continuous data integration, adaptive learning, behavioral support, and emotional responsiveness that together sustain long-term intervention success.

The integration of AI with mobile health applications has created comprehensive platforms that combine multiple intervention components, including dietary tracking, physical activity monitoring, goal setting, progress visualisation, and social networking features. These applications utilise machine learning algorithms to analyse user behaviour patterns, identify potential barriers to success, and proactively provide support and interventions before problems arise. Predictive analytics can anticipate when users are likely to abandon their weight loss efforts and trigger targeted retention strategies, such as personalised motivational messages, peer connections, or healthcare provider outreach (Fabbrizio et al., 2023).

The evidence base for AI-powered personalised interventions comprises primarily pilot studies, feasibility trials, and a growing number of randomized controlled trials, with overall low-to-moderate certainty due to small sample sizes (median n = 150), short follow-up periods (median 12 weeks), and high attrition rates (30–60 % by 6 months). Study designs show heterogeneity in intervention components, comparison groups (waitlist, standard care, or attention control), and outcome measures. Generalisability is limited by: (a) predominance of younger, technologically proficient participants, (b) underrepresentation of individuals with severe obesity (BMI >40) or significant comorbidities, (c) geographic concentration in North America and Europe, and (d) exclusion of individuals with limited digital literacy or device access. Critical gaps impeding clinical adoption include: (a) absence of head-to-head comparisons between AI-driven coaching and intensive human-delivered behavioral therapy, (b) limited understanding of which patient subgroups benefit most from AI versus human support, (c) insufficient long-term data (>24 months) on weight maintenance, (d) lack of established safety monitoring frameworks for conversational AI agents, and (e) unclear cost-effectiveness compared to

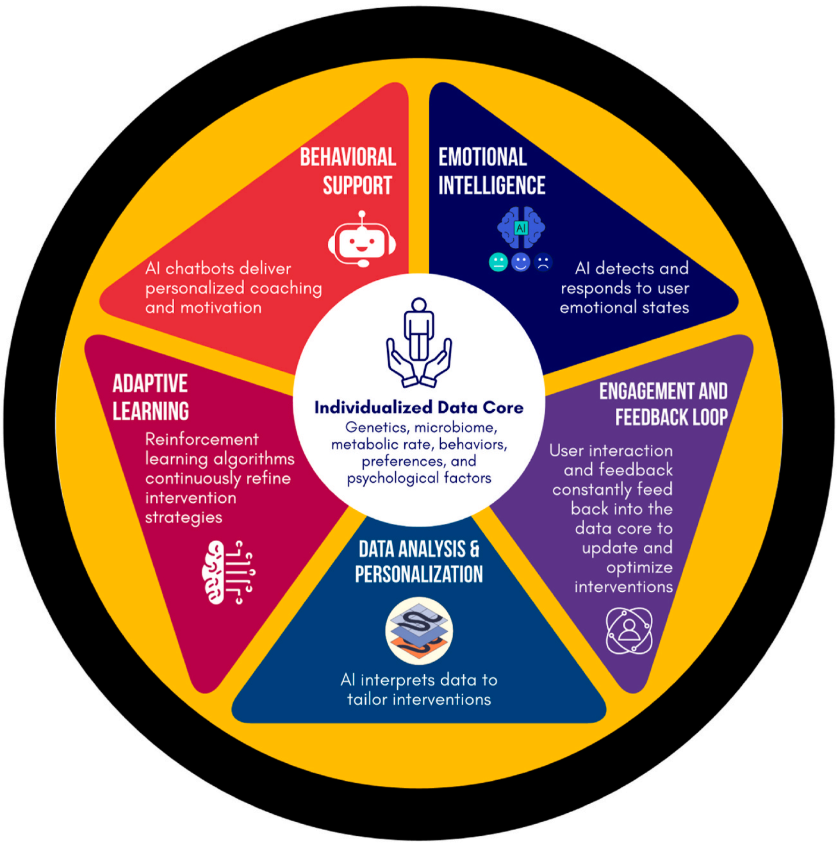

Fig. 2. Cyclical model of AI-driven personalised interventions for obesity management. Centralized individual data informs surrounding adaptive layers of personalised planning, reinforcement learning optimization, AI-powered behavioral coaching, and emotional intelligence. Continuous user engagement creates a feedback loop driving ongoing refinement and sustained adherence.

existing digital health programs.

3.4. Remote monitoring and adherence support

The implementation of AI-enhanced remote monitoring systems has revolutionised the way healthcare providers track patient progress and identify potential issues in obesity management programmes. These systems integrate data from multiple sources, including smart scales, fitness trackers, continuous glucose monitors, smartphone applications, and patient-reported outcomes, to create comprehensive profiles of patient behaviour and progress. Time-series analysis algorithms can detect patterns and trends that may indicate successful weight loss, plateau periods, or potential weight regain, enabling timely interventions to maintain momentum and prevent relapse (Maleki Varnosfaderani and Forouzanfar, 2024).

Predictive analytics algorithms can analyse historical data patterns to forecast individual patient trajectories and identify those at highest risk of treatment failure or dropout. These risk stratification models enable healthcare providers to prioritise their time and resources, focusing intensive support on patients who are most likely to benefit from additional interventions whilst maintaining automated support for those who are progressing well independently. Machine learning models have demonstrated the ability to predict treatment adherence, weight loss success, and long-term maintenance with accuracy rates exceeding 80 %, significantly outperforming traditional clinical assessments (Nwaimo et al., 2024).

The integration of AI with telehealth platforms has created seamless systems for remote obesity management that can provide continuous care without requiring frequent in-person visits. These platforms can automatically analyse patient data, generate progress reports, identify concerning trends, and alert healthcare providers when intervention is needed. Natural language processing algorithms can analyse patient communications, including messages, emails, and survey responses, to identify psychosocial challenges, motivation levels, and potential barriers to success that may require professional attention (Haleem et al., 2021).

Advanced monitoring systems can also provide real-time feedback and coaching to patients based on their current behaviour and progress. For example, if sensors detect that a patient has been sedentary for extended periods, the system can send personalised motivational messages and suggest specific activities based on the patient's preferences and capabilities. Similarly, if dietary tracking indicates poor adherence to recommended eating patterns, the system can provide immediate feedback and alternative meal suggestions that align with the patient's goals and constraints (Li and You, 2022).

Evidence for AI-enhanced remote monitoring derives primarily from observational cohort studies and pragmatic trials, with moderate certainty for technical feasibility but low certainty for clinical effectiveness. Study designs vary considerably in monitoring intensity (daily vs. weekly data collection), intervention triggers (automated vs. clinician-reviewed), and follow-up duration (median 6 months). Generalisability concerns include: (a) selection bias toward motivated, adherent patients willing to engage with monitoring technology, (b) limited evaluation in individuals with multiple chronic conditions requiring complex care coordination, (c) under-representation of older adults and those with physical disabilities affecting device use, and (d) unclear applicability in resource-limited settings with unreliable internet connectivity. Key gaps limiting clinical adoption include: (a) absence of standardized thresholds for clinical alerts and intervention triggers, (b) insufficient evidence on optimal monitoring frequency and duration, (c) limited understanding of provider workload and workflow impacts, (d) lack of integration with existing electronic health record systems, and (e) unclear reimbursement models for remote monitoring services in obesity management.

4. AI-driven digital therapeutics and clinical decision support

4.1. Regulatory-approved digital therapeutics platforms

The emergence of digital therapeutics represents a significant milestone in the integration of artificial intelligence into clinical obesity management, though regulatory status, evidence base, and payer recognition vary considerably across platforms. In the United States, the Food and Drug Administration (FDA) has established pathways for software as a medical device (SaMD), though it is crucial to distinguish between: (a) FDA-cleared or FDA-authorized digital therapeutics with specific indications, (b) programs recognized by the Centres for Disease Control and Prevention (CDC) for diabetes prevention but without FDA medical device authorization, (c) platforms with payer coverage based on clinical evidence without formal FDA review, and (d) research-stage applications without regulatory recognition (Watson et al., 2023).

Omada Health's digital diabetes prevention program is CDC-recognized and has demonstrated clinical effectiveness in multiple randomised controlled trials, but it does not hold FDA clearance or authorization as a medical device for obesity treatment. The platform combines behavioral coaching (delivered by human health coaches supported by AI-powered personalisation algorithms), peer support networks, connected devices (smart scales), and healthcare provider integration to create a comprehensive ecosystem for behaviour change and weight management. Clinical studies have shown that participants in Omada's programme achieve significantly greater weight loss compared to standard care (mean difference of 2–4 % body weight at 12 months), with sustained improvements in metabolic parameters including HbA1c reduction of 0.3–0.4 % in prediabetic populations. Real-world effectiveness studies demonstrate lower retention rates (40–60 % at 12 months) compared to randomized trial settings (60–75 % at 12 months), and cost-effectiveness analyses show mixed results depending on program implementation and healthcare system context (Wilson et al., 2017).

Livongo (now part of Teladoc Health) developed AI-driven platforms that integrate obesity management with diabetes care, recognising the interconnected nature of these conditions and the need for comprehensive metabolic health management. The platform is not FDA-cleared specifically for obesity but operates under established telehealth and remote monitoring frameworks. It utilises predictive analytics to identify patients at risk of complications, personalised coaching algorithms to optimise medication adherence and lifestyle behaviours, and automated clinical escalation pathways to ensure appropriate medical oversight. Real-world evidence studies have demonstrated improved clinical outcomes (HbA1c reductions, increased medication adherence), reduced healthcare costs in employer-sponsored programs, and moderate-to-high user satisfaction rates among participants, though independent long-term validation studies remain limited (Amante et al., 2021).

Noom represents a category of direct-to-consumer digital health applications that incorporate AI-powered features but do not hold FDA authorization as digital therapeutics for obesity. The platform has published evidence from randomized controlled trials and large-scale observational studies showing clinically meaningful weight loss (5–10 % body weight in completers at 6–12 months), though long-term maintenance data beyond 18 months are limited. The platform utilises machine learning algorithms to analyse user behaviour patterns, personalise coaching strategies, and predict which interventions are most likely to be effective for different user profiles. Noom's approach emphasises the psychological aspects of weight management, addressing emotional eating, motivation, and sustainable behaviour change through AI-powered insights combined with human coaching support. Critical evaluation of Noom's evidence base reveals limitations including high attrition rates (60–70 % discontinuation by 6 months in real-world settings), selection bias in published studies toward engaged users, and limited head-to-head comparisons with established behavioral weight loss programs (May et al., 2023).

Currently, no AI-powered obesity management platforms hold FDA clearance or authorization specifically for obesity treatment as a standalone indication. Certain prescription digital therapeutics have received FDA authorization for related conditions (e.g., type 2 diabetes, substance use disorders) that may incorporate weight management components, but these should not be mischaracterized as obesity-specific authorizations. Healthcare providers and patients must carefully evaluate each platform's specific regulatory status, evidence base, and coverage policies to make informed decisions about digital therapeutic selection and integration into care plans.

4.2. Clinical decision support systems

The integration of artificial intelligence into clinical decision support systems has enhanced healthcare providers' ability to deliver evidence-based, personalised obesity management whilst reducing cognitive burden and improving efficiency. These systems analyse patient data from electronic health records, laboratory results, medication histories, and patient-reported outcomes to generate treatment recommendations, identify potential contraindications, and suggest appropriate monitoring strategies. AI-powered clinical decision support can help healthcare providers navigate the complex landscape of obesity treatment options, considering individual patient characteristics, comorbidities, and preferences to optimise treatment selection and dosing (Maleki Varnosfaderani and Forouzanfar, 2024).

Advanced decision support systems can predict treatment responses based on patient characteristics and historical outcomes, enabling more informed treatment selection and realistic expectation setting. Machine learning models trained on large datasets of treatment outcomes can identify which patients are most likely to benefit from specific interventions, such as particular medications, behavioural programmes, or surgical procedures. These predictive capabilities can help healthcare providers and patients make more

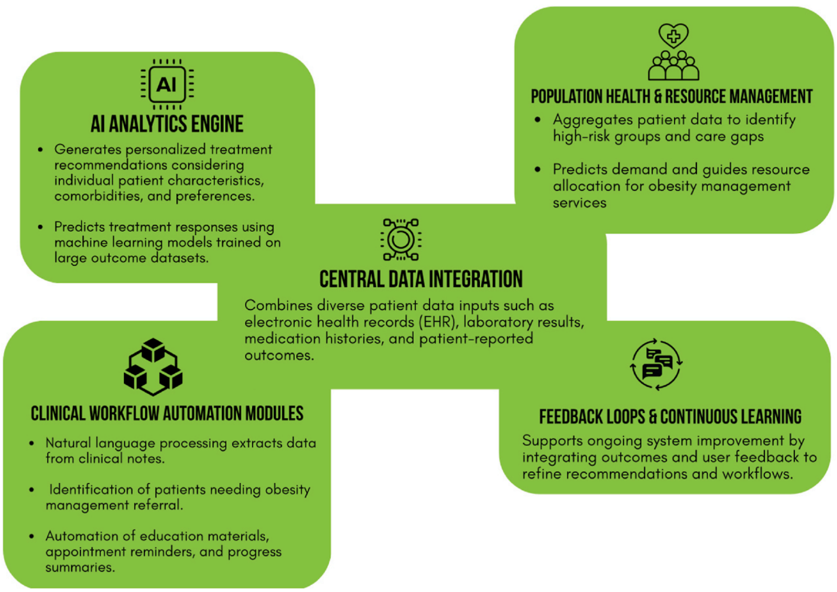

Fig. 3. Conceptual framework of AI-enabled clinical decision support systems for obesity management. The system integrates diverse patient data (including EHR, lab results, medications, and patient-reported outcomes) through an AI analytics engine that delivers personalised treatment recommendations and predicts treatment responses. Clinical workflow automation facilitates data extraction and patient management tasks. Population health analytics support system-level planning and resource allocation. Continuous feedback loops enable ongoing learning and adaptation, collectively augmenting healthcare providers' ability to deliver efficient, evidence-based, and individualised obesity care.

informed decisions about treatment options and resource allocation (Alowais et al., 2023).

The implementation of AI-enhanced clinical workflows has streamlined obesity management processes, reducing administrative burden and improving care coordination. Natural language processing algorithms can automatically extract relevant information from clinical notes and populate structured data fields, whilst machine learning models can identify patients who may benefit from obesity management referrals based on their clinical profiles. Automated systems can also generate patient education materials, appointment reminders, and progress summaries, freeing healthcare providers to focus on direct patient care and complex clinical decision-making (Maleki Varnosfaderani and Forouzanfar, 2024).

Clinical decision support systems enhanced with AI can also facilitate population health management by identifying trends, gaps in care, and opportunities for intervention at the health system level. These systems can analyse aggregate patient data to identify high-risk populations, monitor quality metrics, and guide resource allocation decisions. Predictive analytics can forecast demand for obesity management services, enabling healthcare systems to plan capacity and staffing requirements more effectively (Alowais et al., 2023). As illustrated in Fig. 3, AI-powered clinical decision support systems synthesise multimodal patient data, predictive analytics, workflow automation, and population health management to optimise personalised obesity treatment and healthcare resource planning, thereby enhancing clinician decision-making and efficiency.

The evidence for AI-powered clinical decision support in obesity management consists predominantly of retrospective cohort studies and before-after implementation studies (20 %), with few randomized trials directly evaluating clinical outcomes. Overall certainty is moderate for technical performance (e.g., prediction accuracy, alert precision) but low for impact on patient outcomes (e.g., weight loss, metabolic parameters). Generalisability is constrained by: (a) concentration in large academic health systems with advanced electronic health record infrastructure, (b) limited evaluation in community practice settings with heterogeneous IT systems, (c) variable provider acceptance rates (40–80 %) influenced by alert fatigue and workflow integration, and (d) unclear applicability across different healthcare payment models and practice structures. Critical adoption barriers include: (a) lack of standardized implementation frameworks and interoperability standards, (b) insufficient evidence that AI recommendations improve outcomes beyond existing clinical guidelines, (c) provider concerns about liability and over-reliance on algorithmic suggestions, (d) unclear reimbursement mechanisms for AI-supported clinical decision-making, and (e) limited post-implementation monitoring of system performance and unintended consequences.

5. Benefits and opportunities

5.1. Scalability and accessibility

The scalability advantages of AI-powered obesity management solutions address one of the most significant challenges facing healthcare systems worldwide: the capacity to provide adequate support for the growing number of individuals requiring weight management interventions. Traditional obesity management approaches rely heavily on human resources, including physicians, dietitians, psychologists, and exercise physiologists, whose availability is limited and unevenly distributed geographically. AI systems can provide consistent, evidence-based support to unlimited numbers of users simultaneously, without the constraints of appointment scheduling, geographical location, or healthcare provider availability (Couto and de Almeida, 2025).

The democratisation of obesity management through AI-powered platforms has particular significance for underserved populations, including rural communities, low-income individuals, and those in developing countries where access to specialized healthcare is limited. Mobile health applications powered by AI can deliver sophisticated interventions through smartphones, which are increasingly ubiquitous even in resource-constrained settings. These platforms can provide culturally adapted content, multi-language support, and interventions tailored to local food systems and cultural practices, extending the reach of evidence-based obesity management to populations that have historically been excluded from clinical trials and specialized programs (Asiri et al., 2023).

The cost-effectiveness implications of scalable AI solutions are substantial, particularly when considering the long-term economic burden of obesity-related complications. By providing effective interventions at scale with minimal marginal cost per additional user, AI platforms can achieve favourable cost-effectiveness ratios compared to traditional care models. Economic analyses of digital therapeutics platforms have demonstrated potential cost savings through reduced healthcare utilisation, prevented complications, and improved productivity outcomes, suggesting that AI-powered obesity management could provide positive return on investment for healthcare systems and employers (Horstman et al., 2021).

5.2. Personalisation and precision medicine

Artificial intelligence enables unprecedented levels of personalisation in obesity management, moving beyond the limitations of population-based recommendations to deliver truly individualised interventions. Machine learning algorithms can integrate multiple data streams, including genetic information, metabolome profiles, microbiome composition, behavioural patterns, and environmental factors, to create comprehensive individual profiles that guide treatment selection and optimization. This approach recognises that obesity is a heterogeneous condition with multiple underlying mechanisms, requiring different therapeutic approaches for different individuals (Zeevi et al., 2015).

The integration of precision medicine principles with AI-powered obesity management has led to the development of personalised nutrition recommendations that consider individual metabolic responses to different foods and macronutrient compositions. Studies utilising continuous glucose monitoring combined with machine learning algorithms have demonstrated significant inter-individual variability in glycaemic responses to identical meals, suggesting that personalised dietary recommendations based on individual metabolic profiles may be more effective than standardised approaches. These findings have implications not only for diabetes management but also for weight loss and metabolic health optimization in the broader population (Berry et al., 2020).

Behavioural personalisation represents another frontier where AI can significantly improve intervention effectiveness by tailoring motivational strategies, communication styles, and intervention timing to individual psychological profiles and preferences. Machine learning algorithms can analyse user interactions, response patterns, and engagement metrics to identify which behavioural techniques are most effective for different personality types, cultural backgrounds, and life circumstances. This level of personalisation extends to the timing and frequency of interventions, with AI systems learning optimal contact patterns for each individual to maximise engagement whilst avoiding intervention fatigue (Liu et al., 2023).

5.3. Continuous monitoring and real-time adaptation

The capability for continuous monitoring and real-time adaptation represents a fundamental advantage of AI-powered obesity management systems over traditional episodic care models. Wearable devices and smartphone sensors can collect objective data on physical activity, sleep patterns, eating behaviours, and physiological parameters continuously, providing comprehensive insights into daily life patterns that influence weight management success. AI algorithms can analyse these continuous data streams to identify patterns, trends, and anomalies that may indicate the need for intervention adjustments or additional support (Martín-López et al., 2023).

Real-time adaptation capabilities enable AI systems to respond dynamically to changing circumstances, challenges, and progress, providing just-in-time interventions when they are most needed and likely to be effective. For example, if sensors detect that a user is experiencing increased stress levels or disrupted sleep patterns, the system can automatically adjust goals, provide stress management resources, or modify meal recommendations to account for these factors. This responsive approach acknowledges that weight management occurs within the context of complex, changing life circumstances that require flexible, adaptive interventions (Kroeger et al., 2024).

The integration of predictive analytics with continuous monitoring enables proactive intervention before problems arise, potentially preventing weight regain episodes and maintaining long-term success. Machine learning models can identify early warning signs of treatment adherence decline, motivation loss, or environmental challenges that historically lead to weight regain, triggering preventive interventions such as increased coaching contact, peer support activation, or professional referrals. This proactive approach represents a shift from reactive problem-solving to preventive care that may significantly improve long-term outcomes (Kramer et al., 2023).

6. Challenges and limitations

6.1. Data privacy and security concerns

The implementation of AI-powered obesity management systems raises significant data privacy and security concerns, given the highly sensitive nature of health information, behavioural data, and personal characteristics involved in comprehensive weight management programmes. These systems typically collect and analyse vast amounts of personal data, including medical records, genetic information, eating patterns, physical activity levels, location data, social interactions, and psychological assessments, creating comprehensive digital profiles that could be extremely valuable to unauthorised parties and potentially harmful if misused (Shaban-Nejad et al., 2018). The aggregation of diverse data types creates new categories of sensitive information that may not be adequately protected by existing privacy frameworks designed for traditional medical records.

The involvement of third-party technology companies in AI-powered health applications introduces additional complexity to data governance and privacy protection, as these entities may not be subject to the same regulatory requirements as healthcare providers. Many commercial weight management applications operate under business models that involve data monetisation through advertising partnerships, insurance company collaborations, or pharmaceutical industry relationships, potentially creating conflicts of interest between user privacy and commercial objectives. The lack of transparency in many AI algorithms makes it difficult for users to understand how their data is being processed, what inferences are being drawn, and how this information might be shared or used beyond the stated purposes (Murdoch, 2021).

Cross-border data transfers and cloud computing infrastructure utilised by many AI platforms raise additional jurisdictional and regulatory compliance challenges, particularly as different countries and regions implement varying data protection requirements. The European Union's General Data Protection Regulation (GDPR) and similar regulations in other jurisdictions impose strict requirements for data processing, user consent, and data subject rights that may be difficult to implement in complex AI systems that rely on continuous data collection and algorithmic processing. Healthcare organisations and technology companies must navigate this complex regulatory landscape whilst maintaining the functionality and effectiveness of AI-powered interventions (Vayena et al., 2018).

6.2. Algorithmic bias and health equity

Algorithmic bias represents a critical challenge in AI-powered obesity management systems, with the potential to perpetuate or exacerbate existing health disparities if not adequately addressed during system development and deployment. Machine learning algorithms are inherently dependent on the data used for training, and if these datasets are not representative of the full population diversity, the resulting AI systems may perform poorly for underrepresented groups. Historical healthcare data often reflects existing disparities in access to care, treatment patterns, and health outcomes, potentially encoding these biases into AI algorithms that then make biased recommendations or predictions (Obermeyer et al., 2019).

Demographic bias in AI obesity management systems can manifest in multiple ways, including differential accuracy of risk prediction models across racial and ethnic groups, culturally inappropriate dietary recommendations that fail to account for traditional food systems and preferences, and intervention strategies that assume certain socioeconomic conditions or technological capabilities. For example, AI systems trained primarily on data from affluent, educated populations may generate recommendations that are impractical or inappropriate for individuals with limited financial resources, food insecurity, or constrained time availability due to multiple job responsibilities or caregiving obligations (Chen et al., 2021).

The lack of diversity in AI development teams and clinical research populations compounds these challenges, as biases may be inadvertently incorporated into system design, data collection strategies, and outcome measurement approaches. The predominance of certain demographic groups in both technology development and clinical research means that AI systems may be optimised for these populations whilst failing to account for the needs, preferences, and circumstances of more diverse user groups. Addressing these issues requires intentional efforts to diversify development teams, ensure representative datasets, and implement bias detection and mitigation strategies throughout the AI system lifecycle (Rajkomar et al., 2018).

6.3. *Clinical validation and evidence gaps*

Despite the proliferation of AI-powered obesity management tools and platforms, significant gaps remain in high-quality clinical evidence demonstrating their effectiveness, safety, and superiority over traditional approaches. Many AI applications in obesity management have been evaluated through pilot studies, feasibility trials, or observational studies that lack the rigorous methodology, adequate sample sizes, and long-term follow-up necessary to establish clinical efficacy and guide evidence-based practice. The rapid pace of technological development often outpaces the slower process of clinical validation, resulting in AI systems being deployed in real-world settings without adequate evidence of their effectiveness or potential risks (Topol, 2019).

The heterogeneity of AI approaches, outcome measures, and study populations makes it challenging to synthesise evidence across different studies and platforms, limiting the ability to draw definitive conclusions about the overall effectiveness of AI in obesity management. Different studies may use varying definitions of success, different follow-up periods, and different comparison groups, making it difficult to compare results and establish consistent evidence patterns. The lack of standardised evaluation frameworks for AI-powered health interventions further complicates evidence synthesis and regulatory decision-making (Coiera and Liu, 2022).

Long-term effectiveness and safety data are particularly lacking, as most studies of AI obesity management tools have focused on short-term outcomes and have not adequately assessed sustained weight loss, prevention of weight regain, or potential unintended consequences of AI-driven interventions. The dynamic nature of AI systems, which continuously learn and adapt their recommendations based on new data, presents additional challenges for clinical validation, as the intervention being evaluated may change over time, making it difficult to establish consistent evidence for specific AI approaches (Hatherley and Sparrow, 2025).

Table 2 summarises the current evidence landscape for major categories of AI applications in obesity management, highlighting the gaps between technological capability and clinical validation.

6.4. *User engagement and sustained adherence*

Maintaining long-term user engagement represents one of the most significant challenges facing AI-powered obesity management platforms, with studies consistently demonstrating declining usage patterns over time despite initial enthusiasm and positive short-term outcomes. The phenomenon of digital therapeutics attrition mirrors patterns observed in traditional weight management programmes, suggesting that technological solutions alone may not be sufficient to overcome the fundamental psychological and behavioural challenges associated with sustained weight management. Research indicates that user engagement with mobile health

Table 2
Clinical evidence status for AI applications in obesity management.

AI Application Category	Number of RCTs	Largest Study Size	Longest Follow-up	Key Evidence Gaps	Regulatory Status
Risk Prediction Models (Zhou et al., 2021)	65	45,000	3 years	Diverse population validation, Clinical utility	Research use only
Digital Therapeutics (Wang et al., 2023)	31	2500	24 months	Long-term sustainability, Cost-effectiveness	CDC-recognized (selected); FDA-cleared for related indications only
AI Chatbots/Coaching (Aggarwal et al., 2023)	4	1200	12 months	Comparison with human coaches, Engagement retention	Mixed
Wearable Integration (Wang et al., 2022)	12	3227	18 months	Clinical outcome correlation, Behavioural insights	Consumer devices
Clinical Decision Support (Kouri et al., 2022)	60	8000	6 months	Provider acceptance, Workflow integration	Limited deployment
Personalised Nutrition (Robertson et al., 2024)	7	873	24 months	Metabolic validation, Population generalisability	Research stage

applications typically follows a predictable pattern of initial high usage followed by gradual decline, with most users discontinuing regular use within 3–6 months of initial download (Baumel et al., 2019).

The complexity of human behaviour and motivation presents particular challenges for AI systems attempting to provide sustained support for weight management. Unlike other health conditions that may require short-term interventions or have clear endpoints, obesity management requires indefinite behavioural maintenance and continuous motivation, which may exceed the capabilities of current AI technologies to sustain effectively. Users may experience intervention fatigue, becoming less responsive to AI-generated recommendations and motivational messages over time, particularly if the system fails to adapt adequately to changing circumstances and preferences (Neve et al., 2010).

The "novelty effect" associated with new technologies can create initial engagement and positive outcomes that may not be sustainable as the technology becomes routine and loses its appeal. AI systems must continuously evolve and provide fresh, relevant content to maintain user interest, but this requirement conflicts with the need for consistent, evidence-based interventions that have been clinically validated. The balance between innovation and stability presents ongoing challenges for AI platform developers and raises questions about the long-term sustainability of technology-based interventions (Li et al., 2019).

Social and environmental factors outside the control of AI systems significantly influence user engagement and success in weight management, including family dynamics, work stress, economic circumstances, and major life events. While AI systems can attempt to account for some of these factors, their ability to provide meaningful support during major life disruptions or to address complex social determinants of health remains limited. The individualised nature of AI interventions, whilst being a strength in many contexts, may also limit opportunities for social support and community connection that are important factors in sustained behaviour change (Sevild et al., 2020).

6.5. Regulatory and ethical considerations

The regulatory landscape for AI-powered obesity management tools remains complex and evolving, with different jurisdictions implementing varying approaches to oversight and approval processes. The U.S. Food and Drug Administration has developed frameworks for evaluating digital therapeutics and AI-enabled medical devices, but these frameworks continue to evolve as technology advances and new applications emerge. The challenge of regulating AI systems that continuously learn and adapt presents particular difficulties, as traditional regulatory approaches assume static interventions that remain unchanged after approval. The need for post-market surveillance and ongoing safety monitoring of AI systems requires new regulatory approaches that can accommodate the dynamic nature of machine learning algorithms (FDA, 2021).

Ethical considerations in AI-powered obesity management extend beyond traditional medical ethics to encompass issues of algorithmic fairness, transparency, and accountability. The use of AI systems to make recommendations about diet, exercise, and lifestyle choices raises questions about autonomy and the appropriate level of technological influence on personal health decisions. The potential for AI systems to perpetuate weight stigma or reinforce harmful attitudes toward body image and eating behaviours requires careful consideration and ongoing monitoring. Additionally, the collection and analysis of detailed behavioural data raise concerns about surveillance and the potential for this information to be used in discriminatory ways by employers, insurers, or other third parties (Mittelstadt, 2019).

The lack of transparency in many AI algorithms, often referred to as the "black box" problem, creates challenges for healthcare providers and patients in understanding how recommendations are generated and whether they are appropriate for specific circumstances. Explainable AI approaches are being developed to address these concerns, but implementing interpretable AI systems whilst maintaining performance and personalisation capabilities remains an ongoing technical challenge. The need for AI systems to be auditable and explainable is particularly important in healthcare settings where clinical decision-making must be justified and where errors can have significant consequences for patient health and well-being (Holzinger et al., 2017).

International variations in data protection laws, medical device regulations, and healthcare systems create additional complexity for AI obesity management platforms that operate across multiple jurisdictions. The need to comply with different regulatory requirements whilst maintaining consistent functionality and evidence standards presents ongoing challenges for technology developers and healthcare organisations. The lack of international harmonisation in AI healthcare regulation may impede the global deployment of effective AI solutions and create barriers to research collaboration and evidence sharing (Reddy, 2024).

7. Future directions and emerging trends

7.1. Explainable AI and transparency

The development of explainable artificial intelligence represents a critical priority for advancing the clinical adoption and trustworthiness of AI-powered obesity management systems. Current AI models, particularly deep learning algorithms, often operate as "black boxes" that provide accurate predictions or recommendations without offering insights into the reasoning processes underlying these outputs. This lack of transparency creates barriers to clinical acceptance, as healthcare providers require understanding of how AI systems reach their conclusions to integrate these tools effectively into patient care and to maintain professional accountability for treatment decisions (Arrieta et al., 2020).

Emerging approaches to explainable AI in healthcare focus on developing interpretable machine learning models that can provide clear explanations for their recommendations whilst maintaining high performance levels. Techniques such as LIME (Local Interpretable Model-Agnostic Explanations), SHAP (SHapley Additive exPlanations), and attention mechanisms in neural networks are being adapted for obesity management applications to help users and healthcare providers understand which factors contribute most significantly to AI-generated recommendations. These explanatory capabilities are particularly important in obesity management, where treatment decisions often require consideration of complex interactions between biological, psychological, and social factors (Lundberg and Lee, 2017).

The implementation of explainable AI in obesity management could enhance user engagement and treatment adherence by helping individuals understand the rationale behind personalised recommendations and empowering them to make informed decisions about their health behaviours. When users understand why certain dietary changes or activity modifications are recommended based on their specific circumstances and goals, they may be more motivated to implement these changes and maintain long-term adherence. Additionally, explainable AI can help identify potential biases or errors in algorithmic decision-making, enabling continuous improvement of AI systems and ensuring more equitable outcomes across diverse populations (Adadi and Berrada, 2018).

7.2. Federated learning and privacy-preserving AI

Federated learning represents a promising approach to addressing privacy concerns while enabling the development of more robust and generalisable AI models for obesity management. This distributed machine learning approach allows AI models to be trained across multiple institutions or devices without requiring the centralisation of sensitive patient data, potentially enabling larger-scale collaborative research whilst maintaining data privacy and security. In the context of obesity management, federated learning could enable healthcare systems, research institutions, and technology companies to collaborate on AI model development without sharing individual patient information (Li et al., 2020).

The implementation of federated learning in obesity management could facilitate the development of AI models that are more representative of diverse populations and clinical settings, addressing concerns about algorithmic bias and generalisability. By enabling multiple healthcare systems to contribute to model training whilst keeping their data local, federated learning could help ensure that AI systems perform effectively across different demographic groups, geographic regions, and healthcare contexts. This approach could be particularly valuable for developing AI models that work effectively in resource-constrained settings or for underrepresented populations (Teo et al., 2024).

Privacy-preserving techniques such as differential privacy, homomorphic encryption, and secure multi-party computation are being integrated with federated learning approaches to provide additional layers of protection for sensitive health data used in AI model development. These techniques enable AI systems to learn from aggregate patterns in data whilst providing mathematical guarantees that individual privacy is preserved. The combination of federated learning with advanced privacy-preserving techniques could enable unprecedented collaboration in obesity management research whilst addressing legitimate concerns about data privacy and security (Alkhairi et al., 2023).

7.3. Integration with emerging technologies

The convergence of AI with emerging technologies such as augmented reality (AR), virtual reality (VR), and Internet of Things (IoT) devices is creating new possibilities for immersive and comprehensive obesity management interventions. Virtual reality environments can provide realistic simulations for behaviour modification training, such as practising healthy food choices in virtual grocery stores or restaurants, managing social eating situations, or engaging in virtual exercise programmes that make physical activity more engaging and accessible. These immersive experiences, enhanced with AI personalisation algorithms, could provide more effective behaviour change interventions than traditional approaches (Yaw et al., 2025).

Augmented reality applications integrated with AI computer vision can provide real-time feedback and guidance for healthy behaviours in real-world settings. For example, AR applications could analyse food portions through smartphone cameras and provide immediate feedback on caloric content and nutritional information, or guide users through proper exercise form and technique during workout sessions. The combination of AI analysis with AR visualisation could make healthy behaviour guidance more immediate, contextual, and actionable than current approaches (Hung et al., 2017).

The proliferation of IoT devices and smart home technologies creates opportunities for comprehensive environmental monitoring and intervention that extends beyond individual behaviour tracking to encompass household and community-level factors that influence obesity risk. Smart kitchen appliances integrated with AI algorithms could provide cooking guidance, portion control assistance, and nutritional optimization based on individual dietary goals and preferences. Environmental sensors could monitor factors such as air quality, temperature, and lighting that may influence physical activity levels and eating behaviours, enabling more comprehensive and contextual interventions (Minerva et al., 2015).

7.4. Precision medicine and multi-omics integration

The integration of multi-omics data, including genomics, transcriptomics, proteomics, metabolomics, and microbiomics, with AI algorithms represents the frontier of precision medicine in obesity management. Advanced machine learning techniques can analyse complex interactions between genetic predispositions, gene expression patterns, protein profiles, metabolic signatures, and microbiome compositions to identify personalised therapeutic targets and predict individual responses to different interventions. This approach moves beyond traditional risk factors to consider the fundamental biological mechanisms underlying obesity development and maintenance in each individual (Dorner et al., 2023).

Pharmacogenomic applications of AI in obesity management could optimise medication selection and dosing based on individual genetic profiles and predicted drug metabolism patterns. Machine learning algorithms trained on large datasets of genetic variants, drug responses, and clinical outcomes could predict which obesity medications are most likely to be effective and well-tolerated for specific individuals, reducing trial-and-error prescribing and improving treatment outcomes. This personalised approach to pharmacotherapy could significantly improve the effectiveness of obesity medications whilst reducing adverse effects and healthcare costs (Grammatikopoulou et al., 2024).

The development of dynamic biomarker panels analysed through AI algorithms could enable real-time monitoring of metabolic status and treatment response, allowing for continuous optimization of interventions based on biological feedback. Advances in point-of-care testing technologies and continuous monitoring devices could make comprehensive biomarker analysis more accessible and affordable, enabling routine integration of precision medicine approaches into obesity management. AI algorithms could analyse complex biomarker patterns to detect early signs of treatment response, identify optimal intervention timing, and predict long-term outcomes (Flynn and Chang, 2024).

8. Limitations of the review

This narrative review has several important limitations that should be considered when interpreting its findings and conclusions. The rapid pace of technological development in artificial intelligence and digital health means that some recent innovations and research findings may not be fully captured in the available literature, particularly given the publication delays inherent in peer-reviewed research. The field of AI in obesity management is evolving quickly, with new applications, platforms, and research studies emerging continuously, making it challenging to provide a completely current and comprehensive overview of all developments.

The heterogeneity of AI approaches, study designs, outcome measures, and populations across the reviewed literature limits the ability to draw definitive conclusions about the overall effectiveness of AI interventions in obesity management. The lack of standardised evaluation frameworks and outcome measures makes it difficult to compare results across different studies and AI platforms, potentially leading to incomplete or biased assessments of effectiveness. Many studies included in this review were pilot studies, feasibility trials, or observational studies with limited sample sizes and short follow-up periods, which may not adequately represent the long-term effectiveness and real-world performance of AI systems.

Publication bias may influence the findings presented in this review, as positive results and successful AI implementations are more likely to be published than negative or inconclusive findings. This bias could lead to an overly optimistic assessment of AI capabilities and effectiveness in obesity management. Additionally, many AI applications in obesity management are developed and evaluated by commercial entities that may have financial incentives to present favourable results, potentially influencing the objectivity of available evidence.

The focus on English-language publications may have excluded relevant research conducted in other languages or cultural contexts, potentially limiting the generalisability of findings to diverse global populations. Cultural, economic, and healthcare system differences across countries may significantly influence the effectiveness and applicability of AI obesity management solutions, but these variations may not be adequately represented in the reviewed literature.

The technical complexity of AI systems and the multidisciplinary nature of obesity management create challenges in evaluating and synthesising evidence across different domains of expertise. The authors' backgrounds and perspectives may influence the interpretation of technical AI developments and their clinical implications, potentially introducing bias in the assessment of different approaches and applications.

9. Conclusion

Artificial intelligence has emerged as a transformative force in obesity management, offering unprecedented opportunities to address the limitations of traditional approaches through scalable, personalised, and data-driven interventions. This comprehensive review has examined the diverse applications of AI across the obesity management continuum, from risk prediction and early detection to personalised interventions and long-term monitoring. The evidence demonstrates significant potential for AI technologies to revolutionise obesity care through enhanced precision, improved accessibility, and continuous adaptation to individual needs and circumstances.

The clinical applications of AI in obesity management have shown promising results across multiple domains, including accurate risk prediction models that outperform traditional assessment tools, sophisticated diagnostic systems that provide detailed body composition analysis, personalised intervention platforms that adapt to individual characteristics and preferences, and comprehensive monitoring systems that enable continuous care and support. Digital therapeutics platforms that have received regulatory approval demonstrate the maturation of AI technologies from research prototypes to clinically validated therapeutic tools, whilst emerging applications in precision medicine and multi-omics integration point toward even more sophisticated and effective future interventions. Digital therapeutics platforms vary in their regulatory recognition, with some receiving CDC recognition for diabetes prevention programs while others remain without FDA authorization for obesity treatment, though several demonstrate clinical effectiveness in randomized controlled trials. Emerging applications in precision medicine and multi-omics integration point toward even more sophisticated and effective future interventions, though these remain largely in research stages.

However, significant challenges remain that must be addressed before AI can be fully integrated into routine obesity care. Data privacy and security concerns, algorithmic bias and health equity issues, limited clinical validation evidence, user engagement challenges, and complex regulatory and ethical considerations all represent substantial barriers to widespread implementation. The current evidence base, whilst promising, is characterised by heterogeneous study designs, limited long-term follow-up, and potential publication biases that limit the ability to draw definitive conclusions about AI effectiveness and safety.

The successful integration of AI into obesity management will require coordinated efforts across multiple stakeholders, including healthcare providers, technology developers, researchers, regulators, and patients themselves. Healthcare systems must develop frameworks for evaluating, implementing, and monitoring AI technologies whilst ensuring appropriate clinical oversight and patient safety. Technology developers must prioritise transparency, equity, and evidence-based validation in their product development processes. Researchers must conduct rigorous, long-term studies that adequately assess both benefits and risks of AI interventions across diverse populations and real-world settings.

Future developments in explainable AI, federated learning, privacy-preserving technologies, and precision medicine integration offer promising pathways for addressing current limitations and expanding the capabilities of AI-powered obesity management. The convergence of AI with emerging technologies such as virtual reality, augmented reality, and Internet of Things devices creates new possibilities for immersive and comprehensive interventions that could significantly enhance the effectiveness and engagement of obesity management programmes.

The ultimate success of AI in obesity management will be measured not only by technological sophistication or clinical efficacy but by its ability to reduce health disparities, improve access to effective care, and contribute to better health outcomes for all populations affected by obesity. Achieving these goals will require sustained commitment to addressing the technical, clinical, ethical, and social challenges identified in this review, whilst maintaining focus on the fundamental objective of improving human health and well-being through innovative, evidence-based, and equitable healthcare solutions.

The field of AI in obesity management stands at a critical juncture, with significant technological capabilities developed but substantial work remaining to translate these innovations into routine clinical practice. The evidence reviewed suggests that AI has the potential to transform obesity care, but realising this potential will require continued research, development, and collaboration to address current limitations and ensure that AI technologies serve the needs of all individuals affected by obesity, regardless of their demographic characteristics, socioeconomic status, or geographic location.

CRediT authorship contribution statement

Jennifer Teke: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Maines Msiska:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Oluronke Abisoye Adanini:** Writing – review & editing, Writing – original draft, Investigation. **Eghosasere Egbon:** Writing – review & editing, Visualization, Methodology, Investigation. **Augustus Osborne:** Writing – review & editing, Writing – original draft, Methodology. **David B. Olawade:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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