LOKMAN HEKIM HEALTH SCIENCES

DOI: 10.14744/lhhs.2026.66601
Lokman Hekim Health Sci 2026;6(2):00–00

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REVIEW

Artificial Intelligence–Driven Weight Management: Current Evidence and Clinical Implications

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Abstract

Obesity remains one of the most urgent global public health challenges, necessitating innovative and scalable strategies for effective weight management. This narrative review aims to synthesize current evidence (2021–2026) on the role of artificial intelligence (AI) in weight loss and obesity management, and to evaluate its clinical potential, limitations, and future directions. Recent advances in AI, including machine learning and deep learning techniques, have introduced novel opportunities for personalized nutrition, predictive modeling, and digitally supported behavioral interventions. The literature indicates that AI-driven systems show substantial potential in predictive weight loss modeling, reinforcement learning–based treatment optimization, digital coaching platforms, and biomarker-integrated personalization strategies. Importantly, while AI technologies may enhance scalability and personalization, they should be positioned as clinical decision-support tools rather than replacements for dietitians and healthcare professionals. However, the field remains heterogeneous, with a limited number of long-term randomized controlled trials, variable methodological transparency, and insufficient external validation of predictive models. While AI technologies may enhance scalability and personalization, they should be positioned as clinical decision-support tools rather than replacements for dietitians and healthcare professionals. Ethical considerations, data governance, and algorithmic transparency remain critical for safe and responsible implementation. Overall, AI represents a promising adjunct in weight management; however, its integration into clinical nutrition practice requires rigorous validation and interdisciplinary collaboration.

Keywords: Artificial intelligence; Digital health; Machine learning; Obesity management; Weight loss

Modern lifestyle trends, including physical inactivity and unhealthy dietary patterns, have been strongly associated with obesity, a major health condition that substantially increases the risk of multiple pathologies.[1] Today, obesity represents one of the most critical global pandemics facing society, with prevalence rates reaching alarming and unacceptable levels worldwide.[2] The seriousness of this issue was explicitly recognized at the 75th World Health Assembly in 2022, where Member States endorsed new recommendations for obesity prevention and management and approved the World Health Organization's Acceleration Plan to Stop Obesity. Without effective action against obesity, achieving the target of reducing premature mortality from non-communicable diseases (NCDs) by 30% by 2030 appears unlikely.[3] These developments clearly demonstrate that obesity is not merely an individual health concern but a deepening global public health crisis that demands innovative and systemic solutions.[4]

Cite this article as: *Servi NN. Artificial Intelligence–Driven Weight Management: Current Evidence and Clinical Implications. Lokman Hekim Health Sci 2026;6(2):00–00.*

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E-mail: nursenanahya@gmail.com **Submitted:** 05.03.2026 **Revised:** 19.04.2026 **Accepted:** 30.04.2026 **Available Online:** 21.05.2026

Projections from the World Obesity Atlas 2025 further underscore the magnitude of the problem. By 2030, approximately 50% of adult men and women are expected to have an elevated body mass index (BMI). Obesity prevalence is projected to reach 17% among men and 22% among women. Absolute number projections suggest that more than 2.9 billion adults worldwide will be living with high BMI by 2030, including approximately 1.1 billion individuals with obesity (BMI ≥30 kg/m^2), of whom an estimated 487 million will be men and 643 million women. Notably, the number of individuals with class II obesity or higher (BMI ≥35 kg/m^2) is expected to approach 400 million, with women constituting the majority of this group. These projections are critically important for healthcare planning and resource allocation, particularly given that two-thirds of adults with BMI ≥35 kg/m^2 are anticipated to reside in low- and middle-income countries.[5] This trend indicates that the demand for obesity-related clinical interventions will intensify globally, disproportionately burdening resource-constrained health systems.

In Türkiye, projections indicate that by 2025, 71% of the adult population will have elevated BMI (≥25 kg/m^2), and 36% will be living with obesity. If current trends continue, the number of adults with high BMI is expected to reach approximately 47.4 million by 2030. A substantial proportion of premature deaths and disability-adjusted life years attributable to high BMI are linked to Type 2 diabetes, cardiovascular diseases, and various cancers, highlighting obesity's central role in the burden of NCDs.[5] Although the state plays an important role in combating obesity in Türkiye, its failure to fully adopt the advanced health policies and long-term strategic approaches seen in Europe has led to structural deficiencies in effectively tackling obesity.[6] Collectively, these data demonstrate that obesity cannot be explained solely by individual choices; rather, health-related behaviors must be addressed within a multidimensional and systemic framework.

Health-related behaviors play a fundamental role in improving population health globally. Adherence to healthy dietary patterns, sufficient physical activity, adequate sleep, and avoidance of risk behaviors such as smoking significantly reduce the risk of chronic diseases and all-cause mortality, while also exerting positive effects on mental health. Nevertheless, unhealthy behaviors remain highly prevalent and continue to impose a substantial burden on healthcare systems. In this context, dietitians – who provide evidence-based approaches to the regulation of nutritional behaviors – occupy a pivotal role in supporting sustainable health behavior change.[7]

Nutrition and dietetics constitute a critical discipline in the prevention and management of obesity and obesity-related chronic diseases in modern societies. Irregular eating habits driven by demanding work environments, increased consumption of ultra-processed foods, and sedentary lifestyles have further amplified the importance of dietitians in promoting sustainable healthy living.[8–10] Beyond disease prevention, nutrition is increasingly recognized as a cornerstone of treatment, with the "food as medicine" paradigm suggesting that dietary interventions may offer safer and more sustainable solutions in obesity management compared with purely pharmacological or surgical approaches.[11,12]

Within this framework, dietitians are positioned as essential primary healthcare providers capable of delivering equitable, respectful, and effective care to individuals with overweight or obesity. Strengthening dietitians' education and professional competencies is crucial to implementing person-centered approaches that account for the biological, behavioral, and environmental determinants contributing to excess weight.[11]

Despite the growing global burden of obesity, traditional weight management approaches based solely on conventional dietitian counseling may exhibit limited long-term effectiveness in certain contexts. Standardized "one-size-fits-all" nutritional interventions often fail to adequately capture interindividual biological, behavioral, and environmental variability, thereby limiting sustainable outcomes. This reality underscores the need to support dietitian-led services with more personalized, dynamic, and continuously monitored models of care.[8,13,14]

In recent years, rapid advances in digital health technologies have positioned artificial intelligence (AI) as a promising complementary tool in dietetic practice. AI-based systems have demonstrated potential in generating individualized nutrition recommendations, supporting behavior change, monitoring physical activity, and predicting weight loss success.[15] However, despite its promising role in combating obesity, significant gaps remain in the literature regarding its practical implementation. The majority of studies have focused primarily on obesity detection, whereas prevention and long-term management strategies remain underexplored.[16] By leveraging the capacity to analyze large-scale datasets and provide individualized feedback, AI-based approaches may contribute to the development of more effective, sustainable, and scalable dietitian-guided obesity management strategies.[15]

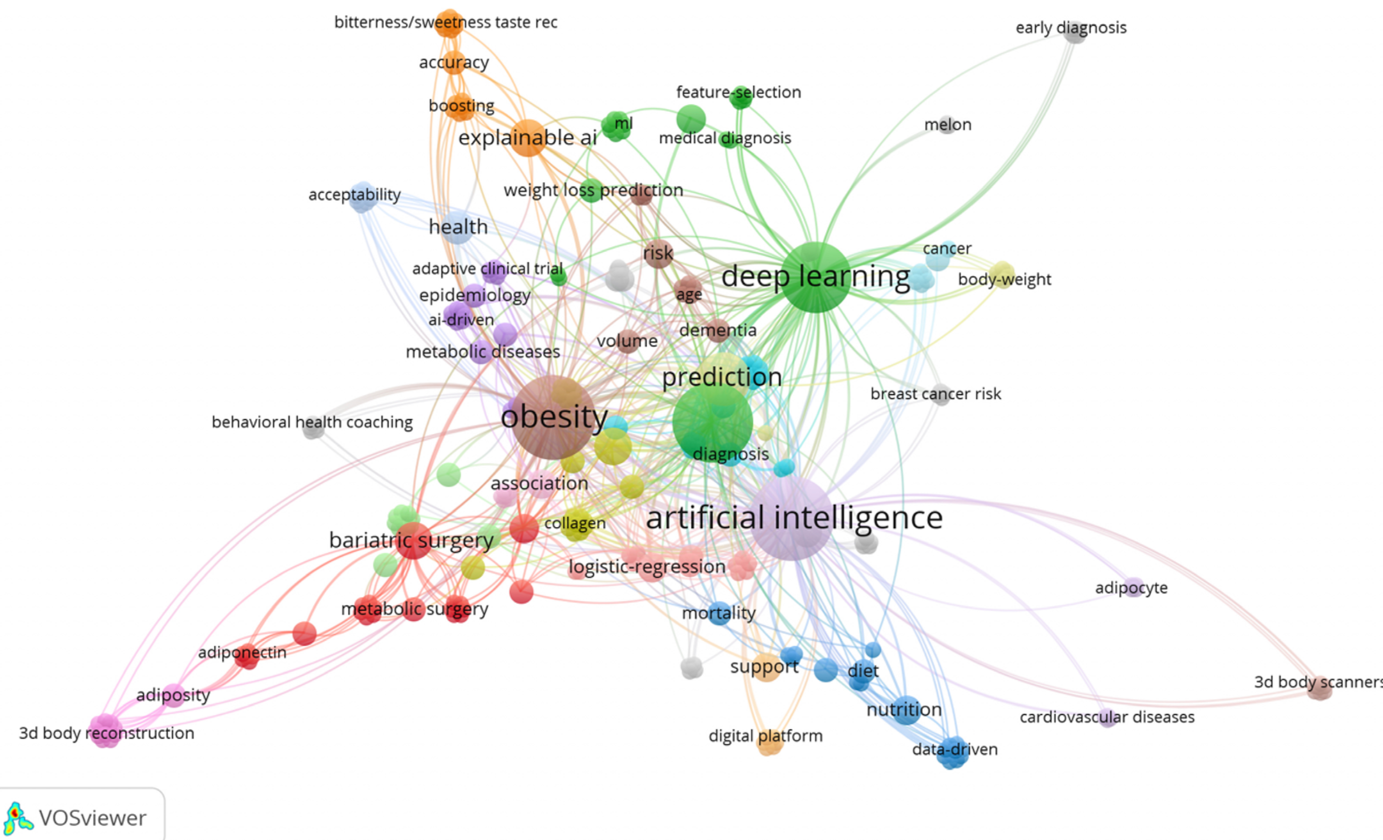

Figure 1. Keyword co-occurrence network based on Web of Science–indexed publications addressing artificial intelligence applications in obesity and weight loss. The network visualizes conceptual relationships among keywords extracted from the literature. Node size represents keyword frequency, link thickness reflects the strength of co-occurrence, and colors indicate major thematic clusters within the research field.

The aim of this narrative review is to critically evaluate current evidence on AI –driven weight management, with a focus on its clinical applicability, predictive capabilities, and integration into dietetic practice.

Materials and Methods

Review Design

This study was conducted as a narrative review aimed at providing a comprehensive and critical interpretation of recent scientific evidence on the role of AI in weight loss, obesity management, and related lifestyle interventions. Rather than applying a systematic review framework, this study adopts an interpretative approach to synthesize current knowledge, identify emerging trends, and highlight key strengths and limitations within the existing literature.

Search Strategy

Relevant literature was identified through searches in the Web of Science and Scopus databases using the keywords (“artificial intelligence” OR “machine learning” OR “deep learning” OR “AI”) AND (“weight loss” OR obesity OR “body weight” OR “weight management”). The search was limited to articles published in English between 2021 and 2026 to ensure coverage of the most recent developments in AI technologies and their clinical relevance. The literature search was conducted up to April 2026. Studies were selected based on their relevance to the topic, with priority given to research providing empirical findings or substantial conceptual contributions to AI-driven weight management. Both clinical and experimental studies were considered. Unlike applying strict inclusion–exclusion criteria as in systematic reviews, the selection process was guided by the aim of capturing representative and informative studies reflecting the diversity of current research in the field. The findings were synthesized using a thematic approach.

Bibliometric Analysis

To support the methodological framework of this review, a term co-occurrence network was constructed based on the current scientific literature in the field of AI and weight loss. VOSviewer software (version 1.6.20) was used to visualize conceptual relationships and thematic clusters among keywords.

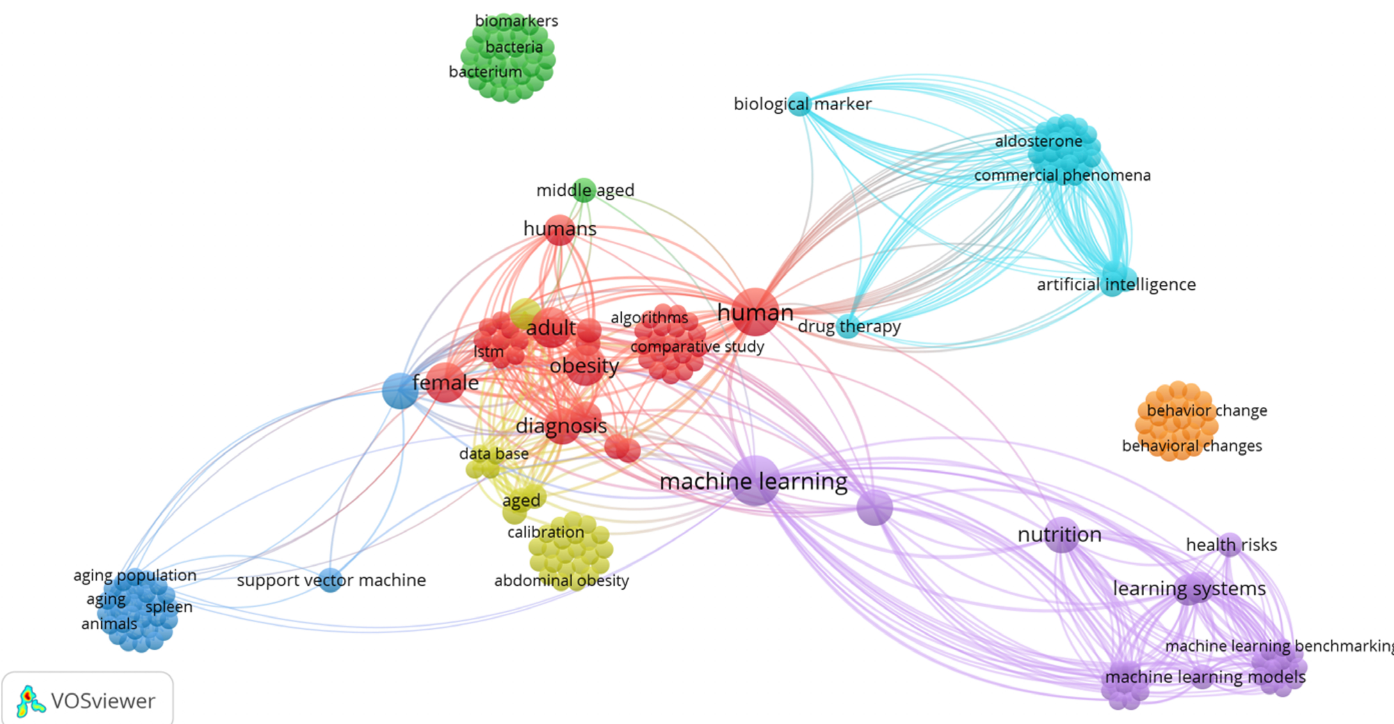

Figure 2. Keyword co-occurrence network based on Scopus-indexed publications examining artificial intelligence–related approaches in obesity and weight loss research. The network illustrates conceptual relationships among frequently co-occurring keywords. Node size represents keyword frequency, link thickness indicates the strength of co-occurrence, and colors denote distinct thematic clusters within the literature.

The visualization presents thematic clusters based on co-occurrence strength, where node size represents term frequency and link thickness indicates the strength of the association between terms. The resulting network structure illustrates how the concepts of AI, machine learning (ML), and deep learning (DL) are positioned within specific thematic contexts in predictive approaches to weight loss in the existing literature.

The dataset used for visualization was retrieved from the Web of Science (Fig. 1) and Scopus (Fig. 2) databases using the expanded search query: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "AI") AND ("weight loss" OR obesity OR "body weight" OR "weight management").

A total of 20,636 documents were retrieved from Web of Science and 8,295 from Scopus (2021–2026, English). Term co-occurrence analysis was performed using a minimum occurrence threshold of 5 and the full counting method. Only terms meeting co-occurrence and connectivity criteria were included in the final visualization. Consequently, 289 items from Web of Science and 279 items from Scopus were retained and visualized as part of the largest connected network.

This bibliometric analysis was used as a complementary exploratory tool to provide insight into the conceptual structure and methodological trends in AI-based weight management research.

Figure 1 presents a Web of Science–based keyword co-occurrence network highlighting the conceptual structure of AI–driven research in obesity and weight loss. The central positioning of AI, obesity, and prediction indicates a strong emphasis on predictive modeling approaches, particularly DL –based methods. Notably, the presence of explainable AI alongside accuracy- and feature selection–related terms reflects a growing interest in model interpretability and clinical transparency. Connections with nutrition, diagnosis, and bariatric surgery further demonstrate the integration of AI applications into both clinical and lifestyle-oriented weight management contexts.

Figure 2 illustrates a Scopus-based keyword co-occurrence network that further refines the conceptual landscape of AI –driven research in obesity and weight loss. In this network, human- and obesity-related terms occupy a central position, closely connected with ML and algorithm-based approaches, indicating a strong focus on human-centered predictive modeling. Distinct clusters related to nutrition and learning systems, biological markers and hormonal pathways, and behavioral change highlight the multidimensional nature of current research. Notably, the separation of clusters associated with biomarkers and behavior change suggests that biological and behavioral components of weight management are often addressed in parallel rather than within fully integrated AI frameworks.

AI and Weight Loss

Conceptual Framework of AI in Nutrition

Although the terms AI, ML, and DL are often used interchangeably today, there is actually a hierarchical relationship between these concepts. AI refers to machines that are programmed to perform tasks that normally require human intelligence, such as pattern recognition, learning from experience, decision-making, and problem-solving, and that can exhibit intelligent behavior. ML is a subfield of AI that enables machines to learn from data without being explicitly programmed and to independently improve their performance over time. DL, as a subfield of ML, focuses on multi-layered artificial neural networks and enables the identification of complex patterns within large data sets. While DL has contributed to significant advances in application areas such as image and speech recognition and autonomous vehicles, interpreting and explaining how these models work remains a major challenge.[17] Beyond the conceptual hierarchy of AI technologies, another critical dimension is the degree of system autonomy in decision-making processes.

Mennella et al.[18] define the autonomy levels of AI systems in five stages from 0 to 4. Level 0 indicates the absence of AI, and standard care is performed entirely by humans; the final decision-maker is human. At Level 1, AI provides recommendations to the system, but the final decision regarding treatment and therapy is made by the clinician. At Level 2, AI generates clinical decisions; however, the process is continuously monitored by humans, and the ultimate responsibility remains with humans. At Level 3, the system makes clinical decisions autonomously, without continuous human supervision; however, human support may be involved in cases of uncertainty. At this level, operational decisions are made by AI, but a human backup mechanism is available. Level 4 represents the highest level of autonomy; AI makes clinical decisions completely independently, and there is no human backup system. At this stage, the final decision-maker is directly AI. In the context of healthcare applications, particularly nutrition recommendation systems, these technological and autonomy distinctions become highly relevant.

Nutrition recommendation systems are classified into three main categories: Knowledge-based, AI -based, and large language model (LLM)-based. Knowledge-based systems offer reliability, transparency, and strong data privacy by relying on established nutrition guidelines; AI-based systems can uncover hidden patterns by processing large volumes of data. LLM-based systems, on the other hand, have the potential to provide personalized nutrition recommendations thanks to their ability to leverage extensive internet resources and interactive communication capabilities.[19]

AI-Supported Interventions and Predictive Personalization in Weight Management

AI-supported personalized nutrition is expected to be one of the greatest revolutions in both nutrition and health. A feasibility study compared manual (questionnaire-based) and wearable sensor-based automatic data collection methods within the scope of a structured weight loss-focused nutritional intervention applied to overweight and obese individuals. At the end of the intervention, participants showed an average weight loss of 2 kg, along with significant improvements in BMI, visceral fat, waist circumference, total cholesterol, and hemoglobin A1c levels. The study demonstrated that data obtained from wearable devices provides a viable and reliable infrastructure for the development and validation of AI-based clinical nutrition applications.[20] While behavioral weight loss, considered the gold standard, achieves clinically meaningful weight loss (7–10%), its high costs and limited scalability make it difficult to reach large populations. It has been demonstrated that a reinforcement learning (RL)-based AI system can allocate limited resources in the most effective and cost-efficient manner by adjusting the intensity of intervention in an individualized and time-sensitive manner. Unlike traditional stepwise care models, RL algorithms can continuously and automatically re-optimize treatment and consider both effectiveness and cost in intervention selection. The findings indicate that this AI-supported approach has the potential to deliver weight loss outcomes comparable to gold standard treatments at a lower cost and to increase the scalability of obesity treatment.[21]

Digital coaching studies show that AI-powered systems, especially when integrated into hybrid human-AI frameworks, can increase both scalability and personalization in weight management. On the online weight loss coaching platform, AI-based optimization methods, including automated food diary feedback and ML -generated meal planning, have been shown to reduce the coach's workload while maintaining the effectiveness of personalized guidance.[4] Importantly, the study did not eliminate human coaching but rather repositioned AI as a layer that enhances efficiency in the interaction process. This demonstrates that algorithmic automation can support operational scalability without compromising the quality of behavioral support. Complementing these findings, generational analyses of AI health coach interactions have revealed nuanced participation patterns across age groups. Although high interaction levels were observed across all generations, participation increased with age, with Boomers (ages 60–78) showing the highest participation and longest interaction duration. Younger users (Generation Z and Generation Y) were more inclined to initiate conversations spontaneously, while older groups predominantly participated in structured, guidance-based interactions. Notably, food diary feedback emerged as the most frequently discussed topic across all generations, reinforcing the central role of diet self-monitoring in AI-supported coaching. These findings emphasize that not only the frequency of interaction but also the style of interaction can influence the effectiveness of AI-focused interventions.[22] Beyond individual platform-based interventions, broader evidence from a comprehensive review further contextualizes the role of text-based AI chatbots in health behavior change. In this review, chatbots were most frequently used as routine coaches (62.8%) or on-demand assistants (27.9%) and generally relied on established behavior change techniques such as cognitive behavioral therapy and goal setting, feedback, monitoring, and social support. Notably, over half of the systems (53.5%) were developed using ready-made, no-code platforms, highlighting the increasing accessibility of chatbot development. Although positive effects were reported in 81.7% of comparisons, only 35.8% showed moderate or large effect sizes, and the evidence remained heterogeneous. Furthermore, while studies primarily focused on physical activity, diet, stress management, and smoking cessation, outcomes related to direct weight management and sleep were relatively underrepresented.[7] In this context, the AI-powered eTRIP application developed for overweight and obese individuals of Southeast Asian origin takes the focus on behavioral self-regulation a step further. The multi-component structure, which combines chatbot-based food trigger queries, food logging using an image recognition system adapted to local foods, and time-based reminders, has led to a significant reduction in overeating and snacking behaviors in a short period of time. The increase in physical activity levels and decrease in depression scores after the intervention suggest that digital self-monitoring tools can affect not only eating behavior but also related psychosocial outcomes. However, the lack of a significant change in anxiety levels and the short duration of the intervention indicate that such applications should be carefully evaluated in terms of long-term clinical outcomes. The low dropout rate (8.4%) and positive user feedback support the system's feasibility.[23]

AI has been applied to weight management through both unstructured real-world data analysis and structured predictive modeling. In the off-label use of semaglutide, AI and natural language processing (NLP)-based analyses of user-generated comments showed that 31.2% reported weight loss, with an average reduction of approximately 26 kg over 3.5 months. Common side effects reported included nausea, vomiting, headache, fatigue, and dizziness, while topic modeling highlighted themes such as dietary changes, cost concerns, and long-term expectations.[24] While these findings provide valuable patient-centered information, relying on self-reported data online leads to potential reporting bias and limits causal interpretation. In contrast, AI models trained on structured digital health records offer a more controlled prediction framework. An XGBoost model built on 121,564 dietary entries from 1,088 individuals with type 2 diabetes predicted ≥3% weight loss with 93% accuracy. Shapley analysis highlighted the role of meal timing, suggesting that AI-supported nutritional analysis could advance diet personalization beyond simple nutrient quantities.[25] However, external validation and cross-population reproducibility are essential for transitioning to clinical practice. Together, these studies demonstrate that AI can both extract experiential signals from real-world patient narratives and generate predictive, personalized dietary strategies. When interpreted in clinically controlled contexts, these complementary approaches can increase precision in weight management.

Predictive modeling approaches clearly demonstrate how AI can develop personalized weight management strategies. In a medical weight management program, baseline variables capable of predicting clinically meaningful weight loss (>10%) over 12 months were identified using ML methods. The random forest model identified quality of life (SF-36 mental and physical scores), age, socioeconomic status, and excess body weight as the strongest predictors of weight loss success.[26] These findings demonstrate that weight loss is strongly linked not only to biometric indicators but also to psychosocial and functional factors. Therefore, considering multidimensional data in initial assessments could provide a significant advantage in planning AI-based personalized interventions.

When transitioning from predictive models to intervention, the clinical outcomes of AI-guided personalized diet support prescriptions were also examined. In a randomized controlled pilot study, the average weight loss at 180 days was 12.3% in the AI group, while it was 7.2% in the physician-guided standard approach, revealing a significant difference of 5.1% between the groups.[27] The rate of clinically significant weight loss (≥5%) reached 83.3% in the AI group, and this approach was associated with a 4.4 times higher probability of success. In addition, more pronounced improvements were observed in BMI, fat mass, and visceral fat indicators. Although both groups followed the same diet and exercise protocol, the holistic integration of genetic, metabolic, and behavioral data through AI appears to have provided an additional benefit. However, due to the pilot design and limited sample size, the results need to be validated in larger populations.

The role of AI in weight management is not limited to individual prediction and intervention; it also extends to the production and optimization processes of nutritional components. A review examining AI-supported bioprocesses for obtaining concentrated nutritional components from different biological sources reports that ML models can increase yield, stability, and bioavailability by predicting process parameters and providing real-time control.[13] This approach is considered important in bridging the gap between biological potential and personalized nutrition applications. However, issues such as regulation, model transparency, scalability, and consumer acceptance remain key obstacles to be overcome in the transition to clinical application.

Similarly, AI-supported medical devices are also emerging as complementary tools for long-term weight management. The ELECT study reported that the use of a non-pharmacological, Food and Drug Administration-approved super-absorbent hydrogel capsule in combination with lifestyle counseling resulted in an average of 11.2% sustained weight loss over 48 weeks.[28] The high compliance rate (>94%) and the absence of serious device-related adverse events suggest that such devices may be safe and tolerable. However, since it is difficult to separate the independent effect of the device from lifestyle counseling, the results must be evaluated within the context of a comprehensive treatment framework.

Studies aimed at capturing the biopsychosocial nature of weight loss at the algorithmic level are also noteworthy. Including sleep quality and stress levels in the artificial neural network model has significantly increased the accuracy of weight loss predictions.[2] When these variables are removed from the model, the significant increase in error rates supports the effect of psychological and behavioral factors on metabolic outcomes.

AI has been increasingly utilized in obesity research for measurement, prediction, and intervention, with numerous studies demonstrating its superior ability to identify clinically meaningful patterns and achieve higher predictive accuracy compared to traditional statistical approaches.[29]

A recent systematic review demonstrated that most AI-based studies focus on identifying obesity risk with high accuracy, while real-world implementation, prevention strategies, and clinical integration remain relatively underexplored compared to predictive applications.[30] This gap highlights a critical translational limitation, as high-performing models do not necessarily translate into effective, scalable interventions in clinical practice. In parallel, emerging evidence indicates that the true transformative potential of AI lies in its ability to integrate multi-omics data, enabling a systems-level understanding of obesity beyond traditional anthropometric measures. AI-driven multi-omics approaches have been shown to improve predictive performance by 5–15% and uncover complex biological interactions across genomic, metabolic, and environmental layers, thereby facilitating more precise risk stratification and personalized intervention strategies.[31] Nevertheless, substantial challenges remain, including data heterogeneity, lack of standardization, limited external validation, and the “black-box” nature of many models, all of which hinder clinical translation. Taken together, these findings suggest that while AI holds considerable promise in obesity management, its future impact will depend on moving beyond isolated predictive models toward integrative, clinically applicable frameworks that combine multi-dimensional data with real-world decision-making processes.

In this context, emerging approaches in the current literature provide concrete examples of how this transformation can be achieved. Specifically, one line of research focuses on the AI-driven identification of neurobiological signatures of obesity and weight loss, while another emphasizes the real-time monitoring of behavioral patterns through internet of things (IoT)-integrated systems.[32–34] Recent evidence further supports the emerging role of AI in uncovering the neurobiological underpinnings of obesity. In a DL–based neuroimaging study, BMI was successfully inferred from structural brain magnetic resonance imaging

(MRI), and importantly, AI-predicted reductions in BMI were significantly associated with actual weight loss following an 18-month lifestyle intervention. Notably, these neural BMI changes were more pronounced in Mediterranean diet–based intervention groups, suggesting that dietary patterns may exert measurable effects on brain structure beyond traditional metabolic outcomes. Moreover, AI-derived BMI estimates were independently associated with key metabolic risk markers, including visceral adiposity, liver fat, insulin resistance, and high-density lipoprotein-C levels, even after adjusting for observed BMI.[33] In parallel, a recent DL study has demonstrated that convolutional neural networks applied to structural MRI data can predict BMI with substantially higher accuracy than traditional ML approaches, suggesting.[34] These findings highlight that AI-driven approaches may capture a broader, neurobiologically embedded phenotype of obesity rather than relying solely on anthropometric measures. However, the relatively modest strength of the association between predicted and actual weight loss indicates that such models should currently be interpreted as complementary tools rather than standalone clinical predictors. In addition, an IoT-integrated framework demonstrated that wearable sensors combined with ML algorithms can accurately classify daily physical activities with high precision (~98%), enabling continuous tracking of physical activity patterns and dietary behaviors. Such systems allow real-time integration of energy intake and expenditure, offering a dynamic perspective on weight management that extends beyond static clinical assessments. Particularly in post-bariatric surgery populations, this approach may provide critical support for long-term adherence to dietary and physical activity recommendations.[32]

From a clinical dietetics perspective, the integration of AI into practice is particularly relevant for patient populations requiring continuous monitoring and individualized intervention, such as those with obesity, Type 2 diabetes, and other metabolic disorders.[35–37] Recent evidence demonstrates that AI-driven systems, including ML- and DL-based tools, enable real-time monitoring, predictive modeling, and personalized treatment planning, thereby improving disease management and patient outcomes. For instance, in diabetes care, AI-supported technologies such as continuous glucose monitoring systems, smart insulin delivery devices, and decision-support algorithms facilitate dynamic adjustment of dietary and pharmacological interventions based on real-time metabolic data.[37]

Beyond diabetes, AI applications extend to broader metabolic disorders, including obesity and metabolic dysfunction-associated conditions, where large-scale data integration from wearable devices, electronic health records, and lifestyle inputs allows for precise risk stratification and tailored nutritional recommendations. These systems can identify high-risk individuals, predict disease progression, and support early intervention strategies, which are critical for long-term dietary adherence and prevention of complications. Furthermore, AI-enhanced mobile applications and digital health platforms have been shown to improve glycemic control, promote weight loss, and support behavioral modification through continuous feedback mechanisms.[35,36]

Taken together, these findings suggest that the most immediate clinical application of AI in dietetic practice lies in high-risk populations requiring sustained lifestyle modification, where continuous monitoring and adaptive, data-driven interventions are essential.

Representative studies highlighting the diversity of AI applications in weight management are summarized in Table 1.

Finally, a recent study shows that the traditional and generalized "total restriction" approach to BMI reduction does not adequately reflect individual response differences. Personalized optimal dietary patterns developed using meta-algorithms have been found to be more effective in reducing BMI compared to general recommendations, highlighting the importance of heterogeneous response patterns in weight management. Notably, the fact that higher consumption of certain foods or beverages is associated with lower BMI in some subgroups suggests that dietary interventions cannot be explained by linear and unidirectional effect assumptions. ML models that predict heterogeneous treatment effects can more clearly distinguish between personalized and general approaches, suggesting that AI -based decision support systems may offer a potential advantage in capturing individual metabolic and behavioral differences.[14] However, such algorithmic outputs should not be evaluated independently of the clinical context, and caution should be exercised when drawing causal inferences. Therefore, AI-based meta-algorithms should not be positioned as tools that will replace dietitians; rather, they should be positioned as decision support systems used under the guidance of dietitians.

A conceptual framework proposed to systematically organize complex AI applications in the literature demonstrates that AI, ML, and DL techniques can be integrated into every stage of the nutrition process.

Table 1. Comparison of the means of lung function parameters of the different categories of Vitamin D level

Lacruz-Pleguezuelos et al.[20]	Randomized crossover controlled trial (feasibility study)	Overweight/obese adults (n=93)	ML-supported wearable integration (CGM, smartwatch, food imaging)	Monitoring	Significant improvements in body weight, metabolic parameters, and glycemic control; ML identified distinct glucose response patterns	Demonstrates the potential of AI-driven wearable systems for real-time monitoring and personalized nutrition strategies
Forman et al.[21]	Randomized controlled trial protocol	Adults with overweight/obesity (planned n=336)	Reinforcement learning (RL)	Decision-making	RL dynamically optimized intervention intensity, achieving comparable weight loss with reduced resource utilization	Demonstrates the potential of AI to optimize treatment allocation and improve cost-effectiveness in weight management
Chew et al.[40]	Single-group pre-test–post-test (mixed methods)	Adults with overweight/obesity (n=230)	Chatbot+computer vision+behavioral nudging	Behavioral intervention	Improvements in overeating, self-regulation, physical activity, and psychological outcomes with high engagement	Demonstrates the potential of AI-assisted behavioral tools for scalable and real-time lifestyle intervention
Pokushalov et al.[27]	Randomized controlled trial	Adults with overweight/obesity (n=60)	Multi-omics AI integration (genetic, metabolic, behavioral data)	Precision treatment	Greater weight loss and improved body composition compared to standard care; higher responder rates	Demonstrates the potential of AI-driven precision nutrition to enhance treatment effectiveness
Alsareii et al.[32]	Framework development study	Not applicable (simulation-based dataset, n=30)	IoT+ML (SVM-based classification)	Monitoring system	High activity classification accuracy (~98.8%) with real-time tracking of diet and physiological data	Demonstrates the potential of integrated AI–IoT systems for continuous monitoring and personalized feedback
Finkelstein et al.[33]	Secondary analysis of RCT (DIRECT-PLUS)	Overweight/obese adults (n=216)	Deep learning (CNN ensemble)+explainable AI	Biomarker identification	Brain-derived BMI predictions correlated with weight loss; distinct neuroanatomical patterns identified	Demonstrates the potential of AI to identify neurobiological signatures of obesity and monitor intervention effects
Cooper et al.[34]	Cross-sectional study (Human Connectome Project)	Healthy adults (n=1106)	Deep learning (3D-CNN)+explainable AI	Neurobiological modeling	High BMI prediction accuracy ($R2\approx0.44$); deep learning captured complex brain–obesity associations	Demonstrates the potential of AI to uncover brain-based biomarkers and advance precision obesity research

AI: Artificial intelligence; ML: Machine learning; DL: Deep learning; RL: Reinforcement learning; IoT: Internet of things; CGM: Continuous glucose monitoring; SVM: Support vector machine; CNN: Convolutional neural network; 3D-CNN: Three-dimensional convolutional neural network; MRI: Magnetic resonance imaging; BMI: Body mass index.

The proposed system begins with personal information, health history, dietary preferences, and lifestyle data obtained from the user. Food recognition and diet tracking are performed using image-based algorithms (e.g., convolutional neural network [CNN], YOLO, Faster R-CNN) and transfer learning models; ML methods analyze food diaries, questionnaires, and wearable device data. This assessment phase is followed by disease risk prediction and personalized nutrition recommendations; algorithms such as random forest, XGBoost, SVM, ensemble methods, NLP, and RL are used here. In addition, genetic analysis and optimization algorithms support personalized meal planning. The process continues through a feedback loop via mobile applications and wearable technologies, ensuring the system is dynamically updated. Ultimately, the proposed framework aims to deliver precise, adaptable, and sustainable personalized nutrition management by combining behavioral insights and multidimensional data analysis.[38]

Collectively, these findings suggest that AI facilitates a multi-dimensional understanding of obesity by integrating genetic, clinical, behavioral, and environmental data, thereby supporting precision-based prevention and personalized management strategies.[39,40]

Limitations

One limitation of this study is the limited number of intervention studies, as well as the predominance of short-term and pilot designs in the existing literature, with a notable lack of long-term randomized controlled trials. This limits the ability to draw robust conclusions regarding the sustainability and long-term clinical effectiveness of AI-driven weight management interventions. Furthermore, many studies are still in the developmental phase. Therefore, no definitive conclusions can be drawn regarding the safety of participants or the effectiveness and accuracy of weight loss outcomes derived from artificial intelligence; these aspects require further evaluation. Another limitation is the language restriction, as studies not published in English were excluded.

In addition, one of the major shortcomings in nutrition research using artificial intelligence is the failure to properly address ethical issues, especially considering the potential for artificial intelligence to function as a dietitian. People should feel secure about how their data will be stored, analyzed, and used. Therefore, we recommend transparency when working with artificial intelligence in the field of nutrition

Conclusion

AI-supported weight management approaches are rapidly evolving from exploratory digital tools to clinically meaningful support systems.

In the field of Nutrition and Dietetics, positioning AI at Level 3 (human-supported autonomy) offers a safer and more sustainable approach. This model supports the decision-making process by establishing a balanced structure between algorithmic efficiency and clinical responsibility while maintaining human oversight. In contrast, Level 4 fully autonomous clinical decision systems harbor significant uncertainties in terms of ethics, legal responsibility, and regulation. Particularly in the field of nutrition, where individual metabolic and behavioral differences are pronounced, fully autonomous systems carry the risk of leading to erroneous generalizations and undesirable clinical outcomes.

The most sustainable and ethically sound model indicated by the literature is a framework in which AI enhances clinical expertise rather than replacing dietitians. Decision support systems, real-time monitoring, and adaptive feedback mechanisms can increase personalization and scalability; however, algorithmic outputs must be evaluated within a clinical, cultural, and ethical context. Professional oversight is indispensable, especially considering risks such as algorithmic bias, data privacy, and misinterpretation of context-disconnected recommendations.

Future research should prioritize large-scale, multi-center randomized controlled trials, external validation of AI models across diverse populations, cost-effectiveness analyses, and the development of clear regulatory frameworks to ensure safe and ethical implementation.

Ethics Committee Approval: As this study is a narrative review based on previously published literature, ethics committee approval was not required.

Conflict of Interest: None declared.

Financial Disclosure: The author declared that this study received no financial support.

Use of AI for Writing Assistance: The author used artificial intelligence (AI)–assisted tools (e.g., ChatGPT Plus) to improve the clarity and readability of the manuscript. The content was critically reviewed, revised, and validated by the author. The author takes full responsibility for the accuracy, integrity, and originality of the work.

Acknowledgments: The author would like to express sincere gratitude to Prof. Dr. Ayla Gülden Pekcan for shaping the selection of this topic.

Peer-review: Double blind peer-reviewed.

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