




Review

# Applying AI Tools for Monitoring Nutrition and Physical Activity in Populations with Obesity: Are We Ready?

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## Abstract

This review examines the current state of development and application of artificial intelligence (AI) tools for monitoring nutrition and physical activity in individuals with obesity, with a focus on the physiological complexity of energy balance and the role of chrono-nutrition. Energy intake and expenditure are dynamically coupled and circadian-regulated: meal timing and movement patterns influence insulin sensitivity, thermogenesis, and Non-Exercise Activity Thermogenesis within the same day. Traditional monitoring methods suffer from recall bias and low granularity, while isolated sensors operate in data silos, limiting accuracy. Effective solutions require multimodal, continuous, and temporally aligned data streams. Current AI models exhibit critical limitations in obesity-specific contexts: inaccurate gait and energy expenditure estimates due to biomechanical differences, dietary models underestimating glycemic variability, poor performance on mixed dishes, sauces, and culturally diverse foods, and a lack of validation against gold standards such as doubly labelled water (DLW) and weighed food records. This review proposes a paradigm shift toward obesity-specific AI design, including enriched datasets and multimodal integration. Physical activity monitoring faces similar challenges: systematic measurement bias in wearables, sensor placement issues, and algorithms trained on normal-weight cohorts. In the GLP-1/GIP era, if transparency, ethical safeguards, and equitable access are ensured, AI will act as a catalyst for personalized care, remote monitoring, trial optimization, and next-generation drug discovery. In conclusion, the integration of AI with rigorous validation procedures and inclusive sampling strategies is essential to achieve reliable, fair, and clinically relevant monitoring approaches for obesity management.

**Keywords:** artificial intelligence; energy balance; chrono-nutrition; dietary monitoring; wearable devices; GLP-1 and GIP receptor agonists; precision nutrition; digital health



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## 1. Introduction

### 1.1. Obesity Within a Dynamic Energy System: Is This a Challenge for AI?

According to the World Health Organization, obesity is classified as a chronic condition characterized by an abnormal or excessive build-up of adipose tissue, which poses significant health risks [1]. From 2021 onward, the European Commission has placed the prevention and treatment of obesity at the forefront of its regional strategy against non-communicable diseases [2]. The Obesity Health Alliance (OHA), whose goal is to

reduce ill-health related to obesity by advocating for evidence-informed policies, outlines in its latest document [3] the established scientific evidence on which policymakers may base their actions. These actions aim to enhance the system of treatment services for individuals living with overweight and obesity. In its recent position statement [3], the OHA underscored the importance of multi-component interventions for the treatment of overweight and obesity, particularly programs combining individual or group sessions with structured exercise classes, psychological support, and motivational interviewing [4–6]. Evidence suggests that multi-component interventions are more effective in weight management across a wide range of age groups than either dietary intervention [7,8] or physical-activity (PA) [6,9,10] intervention alone.

This introduces the concept that energy intake (EI) (i.e., nutrition) and energy expenditure (EE) (i.e., physical activity) are two sides of the same coin in body weight regulation.

In fact, the literature tells us that the concept of a “single strategy” is largely outdated and that effective interventions must consider them in an integrated manner. According to Batsis et al. [5], an intervention combining dietary and exercise components resulted in significant weight loss compared to exercise-only programs in an obese population over 65. While exercise alone improved physical function, it did not lead to significant weight reduction. This is confirmed in pediatric populations by Colquitt et al. [6], who demonstrated that multi-component programs achieve a significantly greater reduction in BMI z-score compared to single interventions (e.g., diet-only interventions). Furthermore, original articles demonstrate the greater effectiveness of multi-component diet and training interventions in body recomposition compared to training alone, both in overweight/obese [11–13] and non-obese [14–17] participants.

This review brings together three interrelated aspects that are frequently addressed separately: (1) the physiological complexity of energy balance and chrono-nutrition, (2) obesity-specific limitations in AI design and validation, and (3) the implications of the GLP-1/GIP therapeutic context for digital health. By synthesizing evidence across these areas, the review outlines key considerations for the development of phenotype-aware and multi-modal AI systems, with attention to ethical requirements and applicability in real-world obesity care.

### *1.2. New Challenge for AI: Do Not Forget the Physiology of Energy Balance and Chrono-Nutrition*

Energy balance is a regulated state emerging from the interplay of energy intake and expenditure, coordinated by neural, endocrine, and behavioural control systems that operate on a circadian timetable. Rather than functioning as a static system, this regulation depends on real-time feedback between eating and movement, in which the direction and degree change across the 24 h cycle. The central clock in the suprachiasmatic nucleus (SCN) aligns the body with the light–dark cycle, while peripheral clocks in the liver, adipose tissue, pancreas, and skeletal muscle associate metabolic programs with feeding–fasting patterns. Light entrains the SCN, but meal timing entrains peripheral clocks, so eating out of phase with the day (e.g., late at night) can desynchronize central and peripheral rhythms and impair metabolic control [18].

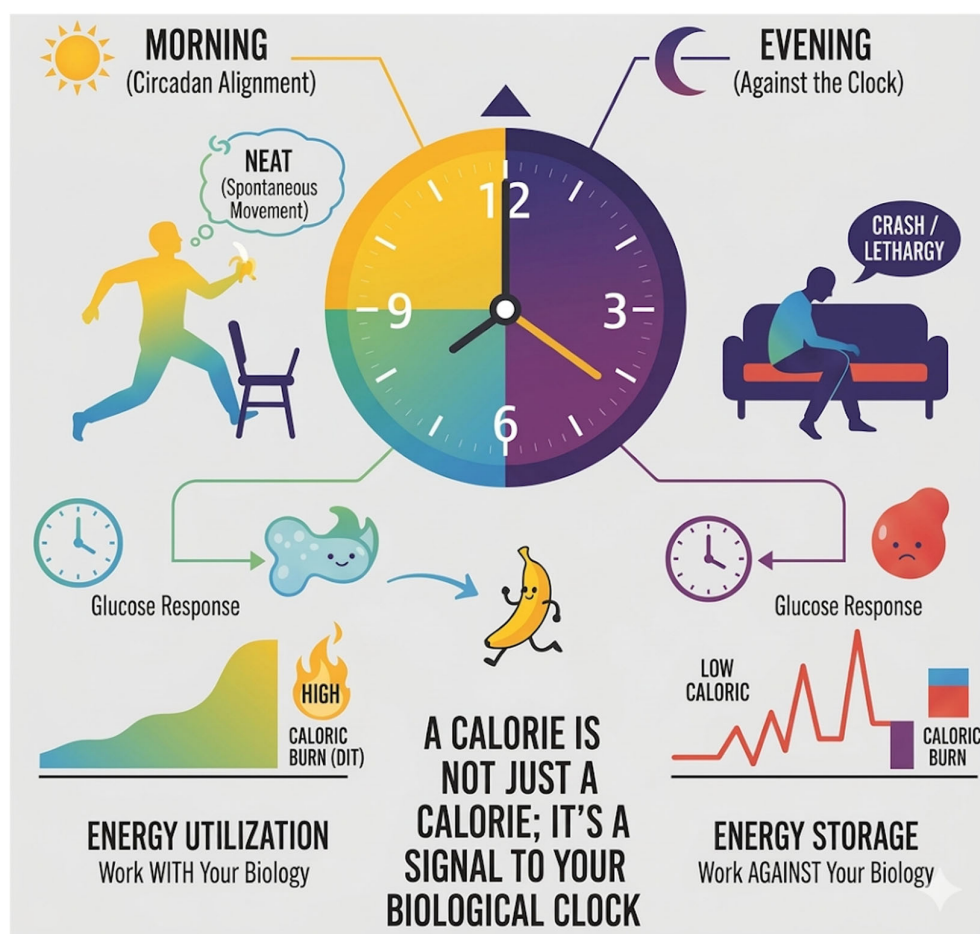
In the hours after a meal, nutrients and gut-derived signals (such as insulin, GLP-1, and PYY) reach hypothalamic circuits (NPY/AgRP and POMC/CART neurons) to suppress hunger and adjust thermogenesis and motor drive. These same signals also reset peripheral clocks, shifting transcriptional programs that govern glucose uptake, lipid handling, and mitochondrial efficiency. It is important to understand the importance of movement in circadian rhythm regulation and calorie utilization. Evidence suggests that early time-restricted eating, where food intake is confined to the morning or early afternoon, offers significant benefits for weight control [19], glycemic regulation [20,21], lipid profiles [22,23], and mi-

tochondrial efficiency [24], even in the absence of caloric restriction, during shift work, compared to late-night eating [25–27]. Physical activity engages metabolic pathways whose efficiency oscillates across the day, and exercise itself can act as a synchronizer, advancing or delaying peripheral clocks depending on timing and intensity [28,29]. Muscle contractions acutely alter circulating substrates and release myokines that signal the energetic state to the brain. A short bout of activity can transiently suppress hunger, whereas sustained or repeated activity tends to raise subsequent appetite to restore balance. Non-Exercise Activity Thermogenesis (NEAT), like fidgeting, standing, and pacing, acts as a high-frequency regulator. When there is an energy surplus, NEAT naturally increases to “burn off” the extra. When there is a deficit of energy, the body tries to save energy by making the person more still. NEAT is the “hidden” variable that bridges the two—it rises when you are metabolically “well-timed” and sinks when your rhythm is disrupted [30]. These principles make chrono-nutrition a powerful lever on the real-time coupling of eating and movement. Early time-restricted eating (eTRE), confining intake to morning or early-afternoon windows, improves insulin sensitivity, lowers blood pressure, and supports weight control even without explicit calorie restriction, while late-day windows are less consistently beneficial. Early TRE produces more favourable glycemic and appetite-hormone profiles, and late isocaloric meals increase hunger, reduce waking energy expenditure, and shift adipose gene expression toward lipogenesis [31]. These effects emerge rapidly, showing that the timing of food intake can influence not only our behavioural patterns throughout the day, such as movement habits, NEAT levels, and activity timing, but also how the body immediately processes those calories, shifting the balance between oxidation and storage within the same 24 h cycle [32]. What is the implication of chrono-nutrition for AI models? These models must integrate circadian timing for accurate predictions. We evolved to be active during the day, and our machinery is most efficient at the start of the light cycle. Insulin sensitivity and diet-induced thermogenesis (DIT) are highest earlier in the morning; identical meals elicit more favourable glycemic and thermogenic responses when consumed in the morning than in the evening [32]. Thus, when we eat immediately modifies how much energy we dispose of as heat versus store as fat and influences our spontaneous movement in the postprandial period [33]. As shown in Figure 1, the body processes the same number of calories differently depending on the biological time of day. For example, morning meals improve insulin sensitivity and thermogenesis, while late meals are associated with reduced glucose tolerance and increased fat storage. This evidence suggests that it is essential for AI models to incorporate and evaluate meal timing to achieve real-life utility.

### *1.3. Why AI Tools Could Be Better: The Limitations of Traditional Monitoring*

Traditional approaches to assessing nutrition and physical activity (PA), such as self-reported food diaries, 24 h recalls, and retrospective PA questionnaires suffer from well-known sources of error, including recall bias, social desirability bias, and high participant burden that erodes adherence over time. These methods provide delayed, low-fidelity feedback that weakens self-regulation loops (from monitoring to feedback and then to adjustment) that are critical for sustained habit formation. Objective devices such as isolated accelerometers and pedometers reduce recall bias by passively capturing movement, but they typically operate without the overview of bodily signals, in data silos, with limited context and weak interoperability with other lifestyle and clinical streams (e.g., diet, sleep, stress, geolocation) [34]. Conventional tools rarely capture these dynamics with sufficient granularity to model inter-individual variability or to support adaptive personalization. This fragmentation blunts the capacity of digital systems to deliver timely, actionable insights or just-in-time adaptive interventions. From a precision nutrition standpoint,

the lack of temporal alignment across data sources is particularly limiting. Personalized recommendations depend on understanding interactions such as nutrient timing relative to PA, compensatory eating after exercise, and short-term fluctuations in energy balance, relationships that require continuous, context-aware sensing rather than retrospective, siloed snapshots. Traditional methods also struggle with interoperability and standardization [35]. Heterogeneous devices impede data integration and reproducibility, undermining cross-study comparability and large-scale learning. These issues have been widely recognized in recent digital phenotyping and evaluation frameworks, which call for open standards, transparent data provenance, and evidence generation approaches that keep pace with rapid software iteration. These limitations underrepresent real-time, feedback-driven behaviour and fail to support modern behaviour-change strategies or precision care. This motivates a shift toward multimodal, continuously connected, and standards-aligned monitoring capable of integrating diet, PA, physiology, and context into interconnected, real-world phenotypes that can inform timely feedback and adaptive interventions [36].



**Figure 1.** The impact of nutrient timing and its implications. The body processes the same number of calories differently depending on the biological time of day. For example, morning meals improve insulin sensitivity and thermogenesis more than late meals, suggesting that AI models should incorporate meal timing.

*1.4. New Challenge for AI: Do Not Forget Nutrition and Physical Activity Tools for the Obesity Condition*

Artificial intelligence (AI) tools for nutrition and physical activity (PA) are often developed using large, general population datasets and marketed as universally applicable. This population-agnostic approach assumes that algorithms trained on broad cohorts can accurately predict behaviours and outcomes across all individuals. However, people living

with obesity present unique behavioural, biomechanical, metabolic, and psychosocial characteristics that challenge this assumption. When models ignore these differences, they risk producing biased predictions and ineffective recommendations [37].

The current literature shows that most AI applications in obesity research focus on detection and classification rather than prevention or personalized management. These models frequently rely on retrospective data from heterogeneous samples, such as national health surveys or electronic health records, without stratifying for obesity-specific phenotypes. As a result, they fail to capture critical nuances in energy balance, movement patterns, and behavioural responses. For example, wearable-based PA algorithms trained on healthy adults often misinterpret gait and energy expenditure in individuals with obesity [38], whose biomechanics differ significantly due to joint loading, altered posture, and mobility constraints. Similarly, dietary prediction models calibrated on average postprandial responses may underestimate glycemic variability and lipid metabolism in obesity, where insulin resistance and visceral adiposity play a dominant role [39].

Behavioural and psychosocial factors further complicate the picture. Individuals with obesity often experience distinct eating behaviours, such as compensatory eating after exercise [40], and face barriers related to stigma, pain, and mental health comorbidities [41]. These factors influence adherence to interventions and responsiveness to feedback loops, yet most AI-driven coaching systems optimize prompts based on patterns observed in general populations [42]. Consequently, interventions designed without accounting for these realities may fail to engage users effectively or even exacerbate disparities.

## 2. Why Are AI Tools Specific to Obesity: The Dietary Intake Monitoring Issue

### 2.1. *Moving Forward, the Critical Gap of Underrepresentation of People with Obesity in Training and Validation Datasets*

Building on the issue of population-agnostic models introduced in Section 1.4, this section delves into the specific consequences of this gap for dietary intake monitoring. A recurrent weakness across the AI–obesity literature is that models are built and tested on convenience samples from general populations (e.g., national surveys, broad EHR cohorts), leading to validity claims that become fragile when applied to underrepresented subgroups. Systematic reviews confirm that detection-style tasks dominate while prevention and management settings—where accurate free-living intake assessment matters most—remain underexplored [37].

Consequently, when these models are used for dietary monitoring in obesity, their accuracy is compromised by the undersampling or poor stratification of this population.

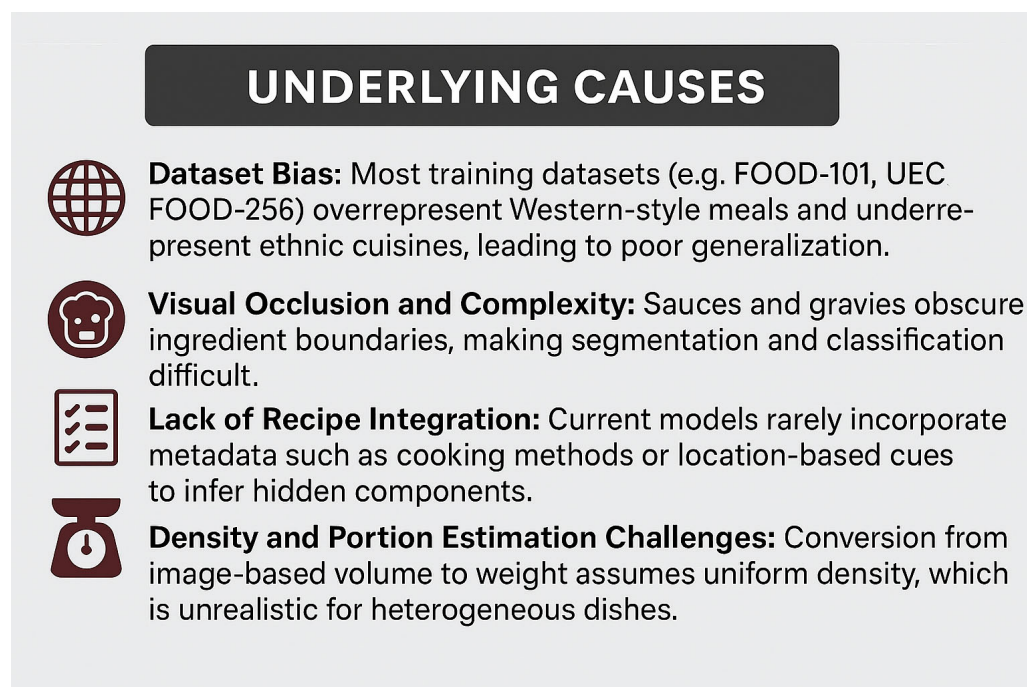
Addressing this data gap requires a multi-pronged approach. First, we need datasets that oversample individuals across BMI classes and metabolic subtypes, integrating multi-modal signals (diet, PA, sleep, stress) with temporal alignment to link, for example, meal timing to glycemic response [43]. Second, validation strategies must evolve from lab-based studies to free-living cohorts enriched for obesity, where challenges like misreporting and comorbidities affect data fidelity. This includes reporting calibration metrics and subgroup performance and using pragmatic trials to assess real-world usability [37]. Ethical considerations—bias auditing, privacy, and equitable access—must guide implementation to avoid reinforcing disparities. Achieving fair and effective AI tools for obesity management requires a shift from generic predictions to precision interventions that reflect the complex realities of the condition. This evolution is essential for translating the AI promise into tangible solutions for prevention and care.

## 2.2. *Moving Forward, the Critical Gap of Poor Performance for Mixed Dishes, Sauces, and Culturally Specific Foods*

Artificial intelligence (AI)-based dietary intake monitoring has advanced rapidly, particularly through image-assisted dietary assessment (IADA) systems that leverage deep learning for food recognition and portion estimation. These systems promise to reduce respondent burden and improve accuracy compared to traditional self-report methods [44]. However, despite notable progress, a persistent and significant limitation remains. In fact, performance is poor when analyzing mixed dishes, sauces, and culturally specific foods. This gap undermines the validity of AI-driven dietary assessment in real-world, free-living contexts, especially among populations with diverse culinary practices, including individuals with obesity. Mixed dishes and sauces are ubiquitous in global diets and often represent major sources of calories, fats, and sodium. For individuals with obesity, these components are particularly relevant because they contribute to energy density and metabolic risk [44]. Misclassification or omission of these elements can lead to substantial underestimation of nutrient intake, compromising both clinical decision-making and research validity. Furthermore, cultural diversity in food preparation—such as regional variations in recipes, hidden ingredients, and complex cooking methods—poses additional challenges for AI systems trained predominantly on Western or standardized datasets [44]. Without addressing these issues, AI-based tools risk perpetuating bias and reducing their applicability in multicultural and obesity-focused interventions. Recent scoping reviews highlight that early IADA systems relied on handcrafted algorithms with limited capacity to handle visual complexity [45]. Although deep learning and convolutional neural networks (CNNs) have significantly improved food identification accuracy for simple, discrete items, performance deteriorates when foods are visually ambiguous or occluded by sauces and garnishes. Multistage segmentation, identification, and portion estimation architectures struggle with overlapping components, while end-to-end models still depend on large, annotated datasets that rarely include culturally diverse or composite meals. Even state-of-the-art systems like goFOOD™ and Im2Calories report higher error rates for mixed dishes compared to single-item meals, despite incorporating advanced techniques such as 3D reconstruction and depth estimation. Moreover, portion estimation for mixed dishes introduces additional complexity. Volume-to-weight conversion requires accurate density values, which vary widely across recipes and cooking methods. Current systems often rely on generic food composition tables, ignoring recipe-specific variations and hidden ingredients such as oils, condiments, and seasonings [46]. This limitation is compounded in culturally specific dishes, where ingredient lists and preparation styles differ substantially from standardized references. The underlying causes are summarized in Figure 2.

To address these limitations, future research must focus on creating solutions that enhance accuracy and inclusivity in AI-driven dietary assessment. A key priority is the development of large-scale, culturally diverse image datasets that include detailed annotations for mixed dishes and sauces, ensuring that models can generalize beyond Western-centric food patterns. Integrating multimodal data sources—such as geolocation, menu databases, and recipe text—will allow systems to infer hidden components and cooking methods, improving the precision of nutrient estimation. Advances in modelling techniques, including multitask convolutional neural networks and generative adversarial networks, offer opportunities to simultaneously predict food identity, portion size, and concealed ingredients within complex meals. Equally important is the implementation of explainable AI frameworks that provide confidence scores and ingredient breakdowns, fostering transparency and trust among dietitians and end-users. Finally, rigorous validation in free-living conditions is essential. Models should be benchmarked against gold-standard

methods such as weighed food records and doubly labelled water, particularly in diverse populations and individuals with obesity, to ensure reliability and clinical relevance.



**Figure 2.** Underlying causes of poor AI performance in dietary intake monitoring for mixed dishes and culturally diverse foods. Key challenges include dataset bias (overrepresentation of Western meals), visual occlusion and complexity (sauces obscuring ingredient boundaries), lack of recipe integration (absence of cooking method and context metadata), and density and portion estimation issues (assuming uniform density for heterogeneous dishes). These factors collectively hinder accurate segmentation, classification, and nutrient estimation in real-world settings.

### 2.3. Moving Forward, the Critical Gap of Limited Validation Against Gold Standards in Obesity

For free living energy intake, doubly labelled water (DLW) is the benchmark for validating total energy intake via energy balance over time, and multi-day weighed food records remain the most reliable source of item- and portion-level truth. Yet, in obesity-focused AI research, gold-standard validation is uncommon, especially among free-living adults with obesity. Most studies still report cross-sectional accuracy against self-reports, laboratory meals, or short controlled protocols, with far fewer directly comparing AI-estimated intake to DLW-derived energy intake or to multi-day weighed records in cohorts intentionally enriched for obesity. Without these rigorous anchors, claims that AI reduces misreporting in obesity are largely aspirational rather than demonstrated [34]. Recent evidence underscores why objective anchors matter [47]. When reported energy intake is evaluated against DLW- and energy-balance-derived energy intake, nearly half of the recalls can be identified as under-reported, and conventional plausibility cut-offs may overlook a substantial proportion of over-reported entries. Approaches that compute measured energy intake from both expenditure (DLW) and changes in body energy stores can reduce bias more effectively than methods that assume energy balance, yet they still do not eliminate error entirely. The choice of validation method, therefore, directly affects both classification and bias estimates, reinforcing that self-report or predicted expenditure cannot substitute for physiologically grounded benchmarks in obesity populations.

This gap mirrors broader challenges in digital phenotyping because there is limited transparency around data provenance and preprocessing, scarce reporting of calibration, and uneven external validation, which keep real-world performance uncertain, precisely

where obesity-related misreporting and contextual complexity (e.g., eating out, mixed dishes, shared plates) are most pronounced [48]. To make longitudinal validation feasible, the field needs open protocols and reproducible pipelines, not just one-off accuracy claims. Therefore, what is needed are prospective, free-living trials in adults with obesity that collect AI dietary estimates in parallel with DLW (to validate total energy intake), embed multi-day weighed intake subsamples (to assert item/portion fidelity), and report agreement, bias, and calibration, stratified by BMI class and food category rather than only overall correlations. A practical roadmap could be the recruitment of obesity-enriched, diverse cohorts with documented cultural food patterns and pre-registered subgroup analyses. The expansion of food-image corpora to include region-specific cuisines, composite dishes, and explicit annotation of sauces/condiments with multi-view captures for scale estimation is also required. The use of hybrid sensing that augments images with contextual signals (time, location, meal timing) and lightweight weight-sensing or utensil cues to better constrain recipe and portion inference, and pair field data with DLW over 7–14 days and integrate weighed record subsamples, should also be considered. It is essential to release protocols, preprocessing code, and model cards with versioned ontologies so historical estimates remain reproducible. Closing these gaps matters because people with obesity experience greater dietary misreporting and face distinct behavioural, biomechanical, and psychosocial realities that shape intake capture. If AI tools are trained on average eaters, optimized for simple foods, and validated without DLW/weighed anchors, they will underperform exactly where accuracy is most critical, obscuring true intake, weakening precision-nutrition counselling, and blunting the effectiveness of weight-management programs. Targeted sampling, culturally aware modelling, and gold-standard, free-living validation offer the most direct path to trustworthy, equitable dietary AI for obesity care.

### 3. Why Are AI Tools Specific to Obesity: The Physical Activity Monitoring Issue

#### 3.1. *Moving Forward, the Critical Gap of Systematic Measurement Bias in Individuals with Obesity*

The most used technology to monitor daily physical activity is wearable technologies that offer the possibility of investigating EE in real-life settings. These devices play a key role in designing and implementing behavioural interventions and physical activity surveillance programs and are widely employed to assess energy expenditure. Body-worn activity monitors hold significant promise due to their user-friendly design and generally acceptable accuracy. However, the body-worn sensors currently in use provide estimates of physical activity that are highly dependent on the specific population.

The population-agnostic bias is equally, if not more, problematic for physical activity monitoring. Here, the systematic measurement error stems from algorithms predominantly developed on normal-weight cohorts, failing to account for the distinct biomechanics and gait patterns of individuals with obesity [49–52]. People with obesity exhibit notable differences in gait and postural control, resting energy expenditure, preferred walking speed, and physical function, which standard algorithms are not designed to handle. This challenge is amplified by the increasing use of both research-grade and commercial multi-sensor wearables in clinical and research settings. Devices from manufacturers such as Apple, Garmin, and Fitbit, which often combine accelerometry with physiological signals (e.g., heart rate), are now widely employed in studies, yet their proprietary algorithms are frequently “black boxes” not validated for specific populations like individuals with obesity. This raises critical questions about the validity of data collected from these populations using standard consumer devices.

Additionally, the placement of wearable devices introduces another potential source of bias in Physical Activity Energy Expenditure (PAEE) estimation. While sensor placement close to the body's centre of mass (COM) effectively captures whole-body motion, the convenience and high compliance of wrist-worn devices have made them the dominant form factor in both research and consumer markets. Biomechanical modifications associated with excess body weight can lead to overestimation of EE when using traditional accelerometry [53]. Que et al. (2025) [54] confirmed that COM-based placements, particularly the three-accelerometer (pelvis + thighs) setup, provided the best estimates of PAEE compared to wrist-based placements. However, the accuracy of hip-mounted activity monitors can be diminished in individuals with obesity, largely due to distinct biomechanical factors like gait patterns and device tilt, introducing greater variability. Multi-sensor armband devices, which combine accelerometer data with other physiological signals like heat flux and skin temperature to improve estimation, also show problematic accuracy in obese individuals [55]. Thus, a significant gap exists: despite the proliferation of wrist-worn commercial devices, researchers and clinicians lack reliably validated, and often transparent, algorithms for estimating EE from these devices specifically for people with obesity.

However, Wei et al. (2025) [56] more recently attempted to fill this gap by developing and validating a novel machine learning algorithm to estimate EE from commercial wrist-worn wearable data. The main result of the study was the development of an algorithm specifically designed to improve EE estimation accuracy for individuals with obesity, a population for which standard algorithms are known to be less accurate. In a lab-based validation with 27 participants (inclusion criteria BMI > 30 kg/m<sup>2</sup>), the algorithm achieved a root mean square error (RMSE) of 0.281 METs at a 60 s window, outperforming most existing hip- and wrist-based ActiGraph algorithms. While this study provides an important open-source algorithm for individuals with obesity, current EE estimation methods face key limitations. Many algorithms are developed and validated using proprietary data or are locked within commercial ecosystems, preventing replication, external validation, and further improvement by the broader research community. Algorithms are often heavily tailored to the specific sensors and placement of a single device. Wei et al. [56] utilized a Fossil Gen 5 smartwatch; while their open-source approach is commendable, the direct applicability of their specific model to data from more ubiquitous devices is not guaranteed and requires further investigation. However, the field still lacks a flexible framework that can integrate data from diverse consumer-grade wearables and generalize across different populations. It is precisely this gap that advanced AI models, with their capacity for multimodal data integration and pattern recognition, are uniquely positioned to fill.

### *3.2. Integration of Nutrition and Physical Activity Data*

The regulation of body weight is a dynamic process governed by the continuous interplay between EI and EE. Despite this intrinsic synergy, most AI applications in health have approached dietary assessment and PA monitoring as independent models. This fragmented approach fails to capture the non-linear and adaptive nature of energy balance in free-living individuals, particularly in the context of obesity management. While isolated models offer valuable insights, the next frontier for precision health lies in the development of integrated, multimodal AI systems. For example, ChatGPT Health is a newly launched feature within the ChatGPT platform designed to provide a dedicated, secure space for health and wellness interactions. It allows users to connect their own health information, such as medical records and wellness app data, to the AI in order to receive more contextually personalized responses to questions about nutrition, exercise, and other aspects of health management. Built with enhanced privacy protections and developed in collaboration with physicians, ChatGPT Health is explicitly intended to support users'

understanding and navigation of health information, not to diagnose conditions or replace professional medical care. Conversations and data within this dedicated space are isolated and are not used to train the underlying models, reflecting a focused effort to balance usefulness with data protection [57]. Pioneering work in multimodal AI integration has demonstrated its potential, primarily in controlled or specific settings. In sports science and performance optimization, models combining biomechanical data, heart rate variability, and nutritional logs have successfully predicted energy expenditure and fatigue risk with enhanced accuracy. A range of technology-centric products and services for managing obesity has emerged in recent years. They are largely available as online and smartphone tools. With them, individuals can input basic data on what they have eaten or intend to eat, and the platform will then estimate the daily calorie deficit or surplus based on their activity levels. Given the large amount of data in the literature and the constant updating of tools, in the following section, we will refer only to reviews from the last year that aim primarily to summarize effective emerging digital trends in obesity management that consider multimodal approaches to EI and PA.

Computational approaches applied to nutrigenomics can elucidate gene–nutrient interactions and guide personalized nutrition. However, challenges related to analytical bias, data privacy, and ethical governance must be addressed. Methodological refinement and responsible implementation are essential for equitable clinical applications [58].

### 3.2.1. What Is Known?

Digital technology, including AI-powered platforms and telehealth systems, facilitates continuous self-monitoring and personalized feedback, improving adherence to weight management protocols [59].

Recent reviews help clarify the current landscape of digital and AI-driven tools. Mobile applications (mHealth) represent the most consistently effective digital approach. Couto et al., in an umbrella review [60], showed a statistically significant, though modest, reduction in body weight (Mean Difference [MD] =  $-1.32$  kg). Long-term eHealth interventions ( $\geq 12$  months) also resulted in significant weight loss (MD =  $-1.13$  kg). Furthermore, eHealth interventions led to significant improvements in BMI (MD =  $-0.58$  kg/m<sup>2</sup>) and waist circumference (MD =  $-1.53$  cm). In contrast, web-based interventions failed to demonstrate a statistically significant effect on weight loss in pooled analyses, despite often including human support elements. The evidence highlights that interventions with structured behavioural components (e.g., self-monitoring, goal setting) and personalized feedback are more effective. Human support (e.g., coaching) is noted as a crucial element for engagement, though not always sufficient for statistical significance in web-based formats [60,61].

The potential of AI to enhance these outcomes lies in its capacity for multimodal data integration. Lee and colleagues [62] report that AI-driven programs can synthesize complex, heterogeneous lifestyle data to enable more precise, real-time personalization. Platforms such as SureMediks have demonstrated promising results, including a 14% body weight reduction and a 2.38% weight loss with a 31% increase in healthy meal consumption in an AI health coach study. Critically, multimodal AI models have shown 6% to 33% performance improvements over unimodal approaches, underscoring the value of data integration [62].

However, the field presents important limitations. AI applications, particularly Large Language Models (LLMs) like ChatGPT, remain investigational. Suenghataiphorn et al. [63] indicate that LLMs may serve as useful adjunct tools for tasks like drafting educational content, but their current limitations preclude autonomous clinical application and underscore the indispensable role of human expertise in obesity management.

Collectively, the evidence indicates that mobile-based interventions with behavioural foundations are currently the most validated digital approach, while AI integration offers promise for enhanced personalization pending further rigorous evaluation.

### 3.2.2. What Is Missing?

The preceding sections have detailed critical gaps in dietary and physical activity monitoring. When we attempt to integrate these modalities for a holistic view of energy balance, these weaknesses are compounded, revealing significant and persistent shortcomings. The field still lacks:

1. **Robust Real-World and Long-Term Evidence:** High heterogeneity in study results questions generalizability, and the modest effect sizes raise concerns about sustained, meaningful clinical impact beyond controlled research settings.
2. **Fragmented and Suboptimal Data Integration:** Key limitations include poor user engagement with digital food diaries (often perceived as unhelpful or shame-inducing), technical barriers to seamless data extraction from wearables, and persistent inaccuracies in self-reported data, compromising the quality of the very data AI models rely on.
3. **Inconclusive and Inequitable Modalities:** Web-based interventions consistently fail to demonstrate statistically significant effects, creating a gap in effective, accessible platform options. Furthermore, variability in digital literacy and access barriers pose critical equity challenges, risking the exacerbation of health disparities rather than their reduction.
4. **Limitations in Personalization and Clinical Utility:** Advanced tools like LLMs show substantial shortcomings in managing complex, individualized clinical scenarios. They exhibit inconsistency, provide generic or inaccurate recommendations, and often fail to tailor advice for patients with specific genetic profiles or multiple comorbidities, highlighting a gap in truly sophisticated, reliable personalization.
5. **Unresolved Ethical and Operational Challenges:** Significant hurdles remain regarding data security, privacy, and the opaque “black box” nature of many AI models, which complicates legal accountability. Furthermore, effectiveness is critically dependent on consistent user engagement, a variable and often unreliable factor, and AI models risk perpetuating biases if trained on nonrepresentative data.

In conclusion, what is missing is a cohesive, evidence-based, and equitable framework that moves beyond proof-of-concept. The field lacks optimized data integration, demonstrably effective and inclusive delivery modalities, robust long-term validation, and transparent, ethically sound AI systems capable of delivering deep, reliable personalization in complex real-world scenarios.

### 3.3. *The Advent of AI as an Enabler of Integration*

The gradual digital revolution in weight control accelerated significantly in 2020 with the emergence of COVID-19, which gave rise to a concrete need for home-based training protocols administered through online platforms and digital strategies to prevent sedentary behaviour.

For instance, a study conducted during the COVID-19 pandemic showed that a structured home-based training protocol administered remotely via an online platform was effective in preventing a sedentary lifestyle, encouraging positive body recomposition with consequent body weight control, highlighting the practical potential of integrated remote monitoring systems in different populations like adults [64–66], young people [67,68], or people with disease [69]. The effectiveness of digital interventions in promoting physical activity and preventing youth obesity is supported by a growing

body of international evidence. Researchers demonstrated the potential of an addiction model-based mHealth intervention [70] and established the feasibility of game-based applications [71,72], smartphone programs [73], and social network interventions [74] for increasing physical activity and preventing early obesity. Building on this evidence, European initiatives are now emerging, outlining a forthcoming European project aimed at preventing sedentary lifestyles and weight gain through a mobile application [75]. This reflects Europe's growing commitment to developing context-specific digital obesity prevention interventions.

Starting from this awareness that multi-component interventions are the most effective in managing obesity, the current challenge with digitization and the use of artificial intelligence is to create AI tools that will not just be an incremental improvement, but a paradigm shift, enabling the first truly simultaneous, continuous, and personalized monitoring, analysis, and interpretation of nutrition and PA. This approach is necessary to improve the feasibility, effectiveness, and reproducibility of multi-component interventions in routine practice. Based on the reviewed literature [76–78] and the seminal Obesity Medicine Association Clinical Practice Statement (2023) [79], artificial intelligence (AI) is emerging as the critical technological enabler of the long-envisioned integration of multi-component obesity care. The core challenge has shifted from recognizing the need for simultaneous, continuous, and personalized monitoring of nutrition, physical activity, and behavioural factors to operationalizing this complex paradigm in patients' daily lives.

AI, defined as the technological acquisition of knowledge and skill by a non-human device capable of adaptive output based on data input learning, provides the foundational architecture to make this feasible. One of the most notable AI applications to gain widespread attention was Chat Generative Pretrained Transformer (ChatGPT), launched on 30 November 2022 [80]. The following was ChatGPT's answer to the text prompt: "Define Artificial Intelligence in under 40 words" (ChatGPT, personal communication, 10 January 2026).

"Artificial intelligence is the field of creating machines that can perform tasks requiring human-like intelligence, such as learning, reasoning, problem-solving, perception, and language understanding."

We followed the same approach as the Obesity Medicine Association in its Clinical Practice Statement document, dated 4 March 2023, to obtain a similar yet distinct definition. This small example helps us understand how these tools are constantly being updated and, as a result, how reliable they are in providing accurate and consistent answers. AI facilitates integration by acting as a central processing hub for heterogeneous data streams. It enables the synthesis of information from electronic health records, wearable technologies, mobile applications, and remote monitoring devices, creating a unified, dynamic patient profile. This capability enables a more integrated approach to care, addressing key points of fragmentation that current systems often leave unaddressed. This capability is crucial for supporting home-based intervention. Specifically, AI-powered systems can deliver personalized nutritional and physical activity recommendations, provide continuous behaviour coaching via empathetic chatbots, and enhance telemedicine through integrated remote monitoring. Furthermore, AI can automate and streamline the administrative burden, such as scheduling, referrals, and prior authorizations, that often fragments care, allowing clinicians to focus on integrated therapeutic decision-making.

Crucially, this integrative function positions AI to overcome the key logistical barriers that have hindered the real-world implementation of effective multi-component interventions. By making continuous, data-driven personalization manageable and scalable, AI transitions the gold-standard model of obesity management from a theoretical construct to a practical, standardizable clinical reality. However, this integrative potential is contingent on

addressing significant challenges, including data interoperability, algorithmic bias, privacy safeguards, and the preservation of the essential human elements of empathy and clinical judgement within the technologically augmented care continuum.

#### 4. AI Monitoring and the Changing Therapeutic Landscape of Obesity in the Incretins Era

The therapeutic landscape of obesity has undergone a profound transformation with the advent of GLP-1 and GIP receptor agonists (GLP-1/GIP Ras), such as semaglutide (GLP-1 receptor agonists) and tirzepatide (GLP-1 + GIP receptor agonists). These agents, originally developed for diabetes management, have demonstrated unprecedented efficacy in weight reduction, achieving outcomes that rival bariatric surgery. Clinical trials report average weight loss of 15–22%, a milestone that has shifted obesity care from a paradigm of lifestyle modification and modest pharmacotherapy to one of potent, hormone-based interventions. This success has fuelled explosive market growth, with forecasts predicting the GLP-1 segment will surpass \$100 billion by 2030, signalling a new era in obesity treatment [81].

Yet, this pharmacological breakthrough brings its own set of challenges. GLP-1 therapies are costly, often exceeding \$1000 per month, and access remains limited by insurance coverage and supply constraints. Moreover, real-world use has highlighted critical issues beyond weight loss, such as poor adherence, muscle and bone mass loss during rapid weight reduction, and the psychological burden of long-term therapy [82]. These complexities underscore the need for digital innovation and AI-driven solutions to optimize treatment delivery, personalize care, and sustain outcomes over time.

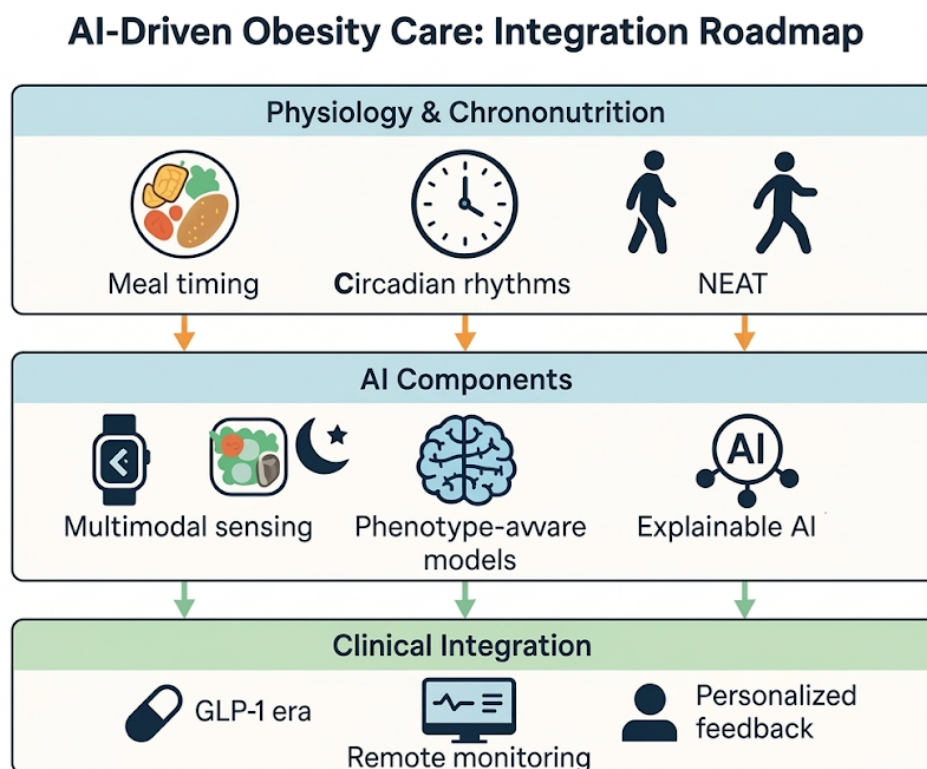
Artificial intelligence is emerging as a pivotal enabler in this evolving landscape. Its role extends across the continuum of obesity care—from drug discovery to clinical monitoring—creating opportunities to enhance precision medicine and patient engagement. In clinical research, AI is streamlining trial design and execution for GLP-1 therapies. As we state, machine learning algorithms now analyze electronic health records to identify eligible participants with remarkable speed and accuracy, while predictive models forecast treatment response across diverse phenotypes. Real-world data platforms aggregate de-identified health records to evaluate drug effectiveness without launching new trials, accelerating evidence generation and reducing costs. These innovations are complemented by remote monitoring technologies, which integrate wearable sensors and smart devices to capture real-time signals of efficacy and safety, such as continuous glucose trends and weight trajectories. Beyond trial optimization, AI is redefining personalized obesity care. GLP-1 therapies, while broadly effective, exhibit significant variability in individual response. AI-driven predictive analytics can identify subgroups—such as patients with “hungry gut” phenotypes—who derive disproportionate benefit from incretin-based drugs. Digital twins and metabolic modelling offer the potential to simulate individual responses, guiding dose adjustments and minimizing adverse effects. Meanwhile, AI-powered behavioural platforms, exemplified by programs like AllurionMeds and Lark Health’s GLP-1 Companion, deliver tailored coaching, monitor mental health, and provide 24/7 support to address adherence challenges and psychological stressors associated with rapid weight loss. The synergy between AI and GLP-1 pharmacotherapy extends upstream into drug discovery. While current GLP-1 analogues dominate the market, AI is accelerating the development of next-generation molecules, including oral formulations and multi-receptor agonists that combine GLP-1 with GIP, glucagon, or amylin for enhanced metabolic outcomes. Deep learning models and generative algorithms are being deployed to design novel peptides and small molecules, predict their safety and efficacy, and optimize pharmacokinetic

profiles—all in silico—dramatically reducing development timelines. Companies such as Novo Nordisk, Eli Lilly, and emerging biotech firms are investing heavily in AI-driven platforms to maintain leadership in this competitive space. Despite these advances, challenges remain. Data scarcity and heterogeneity limit the robustness of AI models, while interpretability concerns hinder regulatory acceptance. Ethical considerations around equity and access persist, as high drug costs and digital divides risk exacerbating disparities in obesity care. Addressing these issues will require transparent algorithms, standardized validation frameworks, and global data-sharing initiatives to ensure that AI enhances, rather than complicates, clinical decision-making.

Looking ahead, the integration of AI with GLP-1-based therapies is expected to influence obesity management by supporting more individualized and data-informed care pathways. Predictive adherence modelling, digital twins for metabolic simulation, and AI-guided mental health support are poised to become standard components of care. As the GLP-1 era matures, the convergence of pharmacology and digital technology offers an unprecedented opportunity to catch up, moving beyond generic weight-loss strategies toward individualized interventions that reflect the complex biological, behavioural, and psychosocial realities of obesity. This transformation could mark the beginning of a new era in chronic disease management, in which the data-driven intelligence and therapeutic innovation work together to provide sustainable health outcomes.

## 5. Conclusions

Artificial intelligence can advance obesity care only if it is built on the physiology of energy balance, aligned with the realities of free-living behaviour, and validated against objective standards. Across this review, three themes consistently emerged: (1) Energy intake and expenditure are coupled and circadian. Chrono-nutrition is not a niche feature; it is a design requirement. The practical implication is that multimodal sensing must be temporally aligned. (2) AI pipelines are not yet obesity-aware. Most existing models were trained and tested on general cohorts and then marketed as universally applicable. In short, AI systems intended for obesity care should be developed, validated, and reported using data derived from populations with obesity. (3) Rigour and equity determine clinical usefulness. Studies should pre-register placement protocols, benchmark against indirect calorimetry or DLW-derived PAEE where feasible, and release population-specific open models so others can reproduce and extend performance. Translating these principles into practice reframes AI from a collection of point solutions into an integrative, phenotype-aware platform for precision care in the GLP-1 era. Incretin-based therapies have changed the trajectory of weight loss and cardiometabolic risk, but AI can add value in predicting responders and non-responders, detecting early signs of intolerance or sarcopenia, delivering just-in-time behavioural support, and integrating digital twins to simulate dose–response under real-world constraints. Critically, these tools must be implemented with transparent model cards, auditable data provenance, privacy safeguards, and equitable access so they reduce disparities. The practical roadmap outlined in Figure 3 summarizes the steps required to operationalize these principles.



**Figure 3.** The proposed integration roadmap for AI-driven obesity care, integrating physiology, multimodal AI components, and clinical application in the GLP-1 era.

## 6. Take-Home Message

AI will move from promise to practice in obesity care when it respects physiology, represents its intended users, and holds itself to objective standards. The field does not need another benchmark that succeeds on simple foods or average bodies. It needs systems that can parse a saucy Sicilian pasta, estimate its impact on this evening's glucose and tomorrow's NEAT, and adapt guidance for a person on GLP-1 therapy with knee pain and night-shift work. That bar is high, but possible. Progress in this field will depend on the use of phenotype-aware data, multimodal and time-aligned modelling, robust validation against gold standards, and transparent approaches that ensure equitable deployment. If the community commits to that agenda, AI will become a dependable co-pilot, really helping clinicians and people living with obesity convert daily choices into durable, personalized health gains.

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## Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
NEAT	Non-Exercise Activity Thermogenesis
DLW	Doubly Labelled Water
GLP-1	Glucagon-Like Peptide-1
GIP	Glucose-Dependent Insulinotropic Polypeptide
PA	Physical Activity
EI	Energy Intake
EE	Energy Expenditure
OHA	Obesity Health Alliance
BMI	Body Mass Index
SCN	Suprachiasmatic Nucleus
NPY	Neuropeptide Y
AgRP	Agouti-Related Peptide
POMC	Proopiomelanocortin
CART	Cocaine- and Amphetamine-Regulated Transcript
DIT	Diet-Induced Thermogenesis
IADA	Image-Assisted Dietary Assessment
CNNs	Convolutional Neural Networks
COM	Centre of Mass
PAEE	Physical Activity Energy Expenditure
MET	Metabolic Equivalent of Task
RMSE	Root Mean Square Error
CDSS	Clinical Decision Support System
XAI	Explainable Artificial Intelligence
SHAP	Shapley Additive Explanations
LLMs	Large Language Models
DTx	Digital Therapeutics
EHR	Electronic Health Record
MD	Mean Difference
HPs	Health Professionals
VLC	Virtual Learning Collaborative

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