



Artificial Intelligence-Assisted Nutritional Counseling for Weight Management in Adult Obesity: A Systematic Review of Randomized Controlled Trials and Primary Studies

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ABSTRACT

Introduction: The global obesity pandemic affects over 2.11 billion adults, with projections exceeding 3.80 billion by 2050. Conventional nutritional counseling modalities face critical limitations in scalability, individualization, and long-term adherence. Artificial intelligence (AI)-assisted nutritional counseling, employing machine learning, deep learning, natural language processing, and reinforcement learning algorithms, represents a transformative paradigm enabling personalized, real-time dietary interventions at population scale.

Methods: This systematic review was conducted following PRISMA 2020 guidelines. Eligible studies comprised randomized controlled trials and primary prospective studies evaluating AI-assisted nutritional interventions in adults (≥ 18 years) with overweight (BMI ≥ 25 kg/m²) or obesity (BMI ≥ 30

kg/m²). Fifteen pre-specified outcome domains were evaluated. Risk of bias was assessed using Cochrane RoB 2.0 and ROBINS-I tools.

Results: Eighteen studies (n=14,732 participants) met eligibility criteria. AI-assisted interventions demonstrated statistically significant reductions in body weight (MD −1.60 kg to −12.3%; 15/18 studies, p<0.01), BMI (MD −0.59 to −1.26 kg/m²; 12/14 studies, p<0.05), HbA1c (MD −0.28% to −2.9%; 9/11 studies), and fasting plasma glucose (7/8 studies). Significant improvements were observed across cardiometabolic, anthropometric, dietary quality, physical activity, health-related quality of life, and patient engagement domains. AI-led interventions demonstrated non-inferiority to human coaching and superiority to standard care.

Discussion: AI-assisted nutritional counseling demonstrates robust, clinically meaningful efficacy across multiple outcome domains. Precision nutrition algorithms integrating postprandial glycemic response prediction and gut microbiome profiling achieved the most comprehensive cardiometabolic optimization. AI-integrated mHealth applications demonstrated superior population-level scalability. Methodological limitations include heterogeneity across AI modalities, short intervention durations, and underrepresentation of low- and middle-income country populations.

Conclusion: AI-assisted nutritional counseling is efficacious, safe, scalable, and non-inferior to human coaching for adult obesity management across ≥10 clinically relevant outcome domains. Integration into multidisciplinary obesity management clinical pathways is recommended, supported by long-term, equity-focused randomized controlled trials with standardized

outcome reporting frameworks.

Keywords: artificial intelligence; machine learning; nutritional counseling; obesity management; precision nutrition

INTRODUCTION

Background and Epidemiology

Obesity (defined as Body Mass Index [BMI] ≥ 30 kg/m²) constitutes one of the most consequential chronic non-communicable diseases (NCDs) of the 21st century, imposing an immense and accelerating global disease burden. According to the Global Burden of Disease Study 2021, the worldwide prevalence of obesity among adults increased by 155.1% in males and 104.9% in females from 1990 to 2021, with an estimated 1.00 billion adult males and 1.11 billion adult females living with overweight or obesity in 2021. Forecasting models project that over 3.80 billion adults—constituting more than half of the global adult population—will have overweight or obesity by 2050, representing a global health emergency of unparalleled magnitude.^{2,3}

The pathophysiologic sequelae of obesity encompass a spectrum of severe cardiometabolic comorbidities including type 2 diabetes mellitus (T2DM), cardiovascular disease (CVD), hypertension, dyslipidemia, non-alcoholic fatty liver disease (NAFLD/MAFLD), obstructive sleep apnea, and at least 13 obesity-associated malignancies, collectively contributing to premature mortality, excess disability-adjusted life years (DALYs), and catastrophic healthcare expenditure. The age-standardized DALYs attributable to high BMI increased by 21.6% in females and 31.2% in males globally between 1990 and 2021, underscoring the urgent imperative for scalable, effective preventive and therapeutic interventions.^{4,5}

Conventional therapeutic approaches to obesity—encompassing behavioral modification, caloric restriction, structured dietary counseling, pharmacotherapy (e.g., GLP-1 receptor agonists, phentermine-topiramate), and bariatric surgery—achieve clinically significant weight loss but are constrained by fundamental structural limitations. Face-to-face nutritional counseling by registered dietitians (RDs) is efficacious but resource-intensive, with patient-to-dietitian ratios frequently exceeding 1,000:1 in public health systems, rendering population-level implementation infeasible. Pharmacotherapy is associated with adverse event profiles and high costs, while bariatric surgery, though the most durable intervention, is accessible to fewer than 1% of eligible candidates globally.

These constraints underscore the critical need for scalable, cost-effective, and sufficiently individualized nutritional intervention modalities capable of reaching the full spectrum of the obese population.^{6,7,8}

Artificial Intelligence in Nutritional Counseling: Conceptual Framework

Artificial intelligence encompasses a constellation of computational methodologies enabling machines to perform tasks requiring human-like cognitive capabilities. In the domain of nutritional counseling and obesity management, AI applications operate through several principal mechanisms: (i) machine learning (ML) algorithms—including supervised learning models (random forests, gradient boosting, support vector machines) and unsupervised clustering—applied to large-scale dietary, metabolic, genomic, and microbiome datasets to predict individual dietary responses and generate personalized recommendations; (ii) deep learning (DL) and convolutional neural network (CNN)-based image recognition systems enabling automated real-time food identification and caloric estimation from dietary photographs; (iii) natural language processing (NLP)-powered conversational agents (chatbots) delivering scalable, real-time dietary counseling through psychologically-informed behavior change frameworks; (iv) digital twin technology utilizing AI-driven CGM data integration to model individualized postprandial metabolic dynamics; and (v) reinforcement learning (RL)-based adaptive intervention systems optimizing real-time behavioral prompts based on ongoing patient engagement data.^{9,10,11}

Precision nutrition—the individualization of dietary recommendations based on multi-omics data (genomics, metabolomics, microbiomics), physiologic phenotyping (continuous glucose monitoring, wearable biosensors), and behavioral profiling—represents the paradigmatic convergence of AI and nutritional science. ML algorithms integrating gut microbiome composition, postprandial glycemic response (PPGR) patterns, and clinical biomarkers have demonstrated capacity to predict individual dietary responses with significantly greater accuracy than population-level dietary guidelines, establishing a mechanistic basis for AI-driven precision nutrition superiority over conventional one-size-fits-all approaches.^{12,13,14}

Research Gap and Novelty

Despite the rapid proliferation of AI-assisted nutritional platforms and mHealth applications, a comprehensive, rigorous systematic synthesis evaluating their clinical efficacy across the full spectrum of clinically relevant outcome domains—spanning anthropometric, glycemic, lipidemic, cardiovascular, behavioral, and quality-of-life dimensions—is conspicuously absent from the literature. Prior reviews have addressed narrow subsets of AI modalities (e.g., chatbots exclusively), specific pathologic populations (e.g., T2DM in isolation), or single primary outcomes (e.g., body weight only), failing to synthesize the multi-domain efficacy profile of AI nutritional interventions as a therapeutic class. Furthermore, comparative analyses between distinct AI technology architectures and between AI-led versus human-led interventions remain insufficiently synthesized to inform clinical decision-making and health system resource allocation.^{15,16,17}

To our knowledge, this is the first systematic review to: (i) simultaneously evaluate ≥ 10 pre-specified clinically diverse outcome domains of AI-assisted nutritional counseling in adult obesity; (ii) include the complete typology of AI modalities—ML-based precision nutrition algorithms, NLP chatbots, AI-integrated mHealth platforms, digital twin systems, AI-guided supplement prescriptions, and virtual reality AI coaching; (iii) perform head-to-head comparative analyses between AI and human-led nutritional interventions and between different AI technology subtypes; and (iv) systematically assess RoB across all included studies using the validated Cochrane RoB 2.0 framework.^{18,19}

Research Objectives

The primary objective of this systematic review is to evaluate the clinical efficacy and safety of AI-assisted nutritional counseling interventions compared to standard care, conventional dietary counseling, or human-led programs in adults with overweight or obesity across ≥ 10 pre-specified clinically relevant outcome domains. Secondary objectives include: (i) characterization of the typology and technical architecture of AI nutritional counseling systems employed in clinical research; (ii) systematic risk of bias assessment across included studies; (iii) identification of moderators of AI intervention efficacy; and (iv) delineation of critical evidence gaps to guide future high-priority research.²⁰

Hypothesis

We hypothesized that AI-assisted nutritional counseling interventions produce statistically significant and clinically meaningful improvements—exceeding established minimum clinically important differences (MCIDs)—in body weight ($\geq 5\%$ reduction), BMI, waist circumference, HbA1c ($\geq 0.5\%$ reduction), fasting plasma glucose, body fat mass, visceral fat, triglycerides, LDL/HDL cholesterol, blood pressure, dietary quality, physical activity, HRQoL, and patient engagement, compared to standard care or conventional dietary counseling in adults with overweight or obesity.^{19,20}

METHODS

Study Design and Registration

This systematic review was designed and reported in strict adherence to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 checklist and explanation document. No quantitative meta-analysis was performed due to anticipated substantial clinical heterogeneity (different AI modality types, population characteristics, intervention durations, and outcome measurement instruments); a rigorous qualitative narrative synthesis with comprehensive tabular data presentation was conducted in accordance with the Synthesis Without Meta-analysis (SWiM) reporting guidelines.^{20,21}

Eligibility Criteria (PICOS Framework)

Population

Adults aged ≥ 18 years with overweight (BMI ≥ 25 kg/m²) or obesity (BMI ≥ 30 kg/m²) as defined by the World Health Organization (WHO) classification. Studies enrolling predominantly T2DM or prediabetes populations were included if participants met BMI eligibility criteria and nutritional counseling was a primary or co-primary intervention component.⁸

Intervention

Any AI-assisted nutritional counseling modality, including but not limited to: (i) ML-based dietary recommendation systems incorporating genomic, metabolomic, or microbiome data; (ii) NLP-powered conversational agents (chatbots) providing dietary advice; (iii) AI-integrated smartphone or web-based mHealth applications with automated personalized feedback; (iv) digital twin platforms generating individualized meal plans via AI-processed CGM data; (v) AI-guided dietary

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supplement prescription systems; (vi) AI-embedded multi-component lifestyle intervention programs with dietary counseling as a core element.^{9,10,11}

Comparator

Standard care (usual dietary advice from general practitioners), conventional dietitian-led nutritional counseling, human coach-led lifestyle programs, non-AI digital platforms, waitlist or attention controls, or alternate dietary approaches (e.g., Mediterranean diet).¹²

Outcomes

Pre-specified primary outcomes: (1) Body weight change (kg or %); (2) BMI (kg/m²); (3) Waist circumference (cm). Pre-specified secondary outcomes: (4) HbA1c (%); (5) Fasting plasma glucose (mg/dL or mmol/L); (6) Body fat mass (kg or %); (7) Visceral fat (rating or area); (8) Triglycerides (mmol/L or mg/dL); (9) LDL cholesterol; (10) HDL cholesterol; (11) Systolic and diastolic blood pressure (mmHg); (12) Dietary quality index; (13) Physical activity level; (14) Health-related quality of life; (15) Patient engagement and adherence.²⁰

Study Design

Randomized controlled trials (parallel-group, crossover, cluster-RCT) and primary prospective studies (quasi-experimental designs with pre–post assessment, single-arm prospective cohorts) published in English between January 2018 and March 2026 were eligible. Case reports, editorials, reviews, conference abstracts without peer-reviewed full text, and animal or in vitro studies were excluded.^{20,21}

Search Strategy

The keywords used for this research based PICO :

Component	Keyword 1	Keyword 2	Keyword 3
P (Population)	Adult Obesity	Overweight Adults	BMI ≥30 kg/m ²
I (Intervention)	AI-Assisted Nutritional Counseling	Machine Learning Dietary Systems	Digital Health Coaching

C (Comparator)	Standard Dietary Care	Human-Led Counseling	Conventional Lifestyle Programs
O (Outcomes)	Weight Loss Efficacy	Cardiometabolic Markers	Patient Engagement & Adherence

The Boolean MeSH keywords inputted on databases for this research are: (*"Adult obesity" OR "Overweight adults" OR "BMI ≥ 30 kg/m²"*) AND (*"AI-Assisted nutritional counseling" OR "Machine learning dietary systems" OR "Digital health coaching"*) AND (*"Standard dietary care" OR "Human-led counseling" OR "Conventional lifestyle programs"*) AND (*"Weight loss efficacy" OR "Cardiometabolic markers" OR "Patient engagement & adherence"*)

Study Selection Process

Titles and abstracts of all retrieved records were independently screened by two qualified reviewers (blinded to each other's decisions) using Rayyan QCRI systematic review software. Full-text articles of all potentially eligible records were retrieved and independently assessed against the pre-specified eligibility criteria. Discrepancies at each screening stage were resolved through structured discussion and, when consensus was not achievable, arbitration by a senior third reviewer. Inter-rater reliability was calculated using Cohen's kappa (κ) statistic. The complete study selection process is documented in a PRISMA 2020 flow diagram.^{20,21}

Data Extraction

Standardized data extraction forms were developed a priori and pilot-tested on five randomly selected eligible studies to optimize reliability. The following data elements were systematically extracted: first author surname, publication year, country of study conduct, study design, funding source, sample size (intervention and control groups), participant demographic and clinical characteristics (age, sex, BMI, relevant comorbidities), AI intervention type and technical description (algorithm type, data inputs, delivery platform), comparator description, intervention duration, follow-up duration, primary and secondary outcome measures with effect sizes (mean differences [MD], odds ratios [OR], hazard ratios [HR]) and 95% confidence intervals (CIs), statistical significance levels, attrition rates, and reported adverse events. Data extraction was performed independently by two reviewers, with discrepancies resolved by consensus.^{20,21}

Risk of Bias Assessment

Risk of bias in included RCTs was independently assessed by two reviewers using the Cochrane Risk of Bias 2.0 (RoB 2) tool, evaluating five domains: D1 – bias arising from the randomization process (sequence generation, allocation concealment); D2 – bias due to deviations from intended interventions (blinding of participants and personnel, adherence to assignment); D3 – bias due to missing outcome data (completeness of outcome data, ITT analysis); D4 – bias in measurement of the outcome (blinding of outcome assessors, outcome assessment method); D5 – bias in selection of the reported result (pre-registration, selective outcome reporting). Each domain was rated as 'Low Risk,' 'Some Concerns,' or 'High Risk,' culminating in an overall RoB judgment. Non-randomized prospective studies were evaluated using the Risk Of Bias In Non-randomised Studies of Interventions (ROBINS-I) tool. Disagreements were resolved by discussion.^{20,21}

Synthesis of Results

Given substantial clinical and methodological heterogeneity precluding pooled meta-analytic estimates, a narrative synthesis framework was employed in accordance with the SWiM guidelines. Findings were organized by pre-specified outcome domain and AI modality type. Within each outcome domain, studies were tabulated by direction and magnitude of effect, statistical significance, and quality of evidence. Subgroup analyses were conducted descriptively, examining effect modification by: (i) AI modality subtype; (ii) intervention duration (short-term: <3 months; medium-term: 3–6 months; long-term: >6 months); (iii) BMI category at enrollment; (iv) presence vs. absence of concurrent human clinical oversight; and (v) clinical setting (outpatient clinic, community, fully remote).^{20,21}

Table 1. Article Search Strategy

Database	Keywords	Hits
Clinicaltrials.gov	("Adult obesity" AND "AI-Assisted nutritional counseling" AND "Weight loss efficacy" OR "Cardiometabolic markers" OR "Patient engagement & adherence")	59
Semantic Scholar	("Adult obesity" OR "Overweight adults" OR "BMI ≥ 30 kg/m ² ") AND ("AI-Assisted nutritional counseling" OR "Machine learning dietary systems" OR "Digital health coaching") AND ("Standard dietary care" OR "Human-led counseling" OR "Conventional lifestyle programs") AND ("Weight loss efficacy" OR "Cardiometabolic markers" OR "Patient engagement & adherence")	250
Science-direct	"Adult obesity" AND "AI-Assisted nutritional counseling" AND "Weight loss efficacy" OR "Cardiometabolic markers" OR "Patient engagement & adherence"	993
Pubmed	("Adult obesity" AND "AI-Assisted nutritional counseling" OR "Machine learning dietary systems" OR "Digital health coaching") AND ("Weight loss efficacy" OR "Cardiometabolic markers" OR "Patient engagement & adherence")	4
Cochrane	("Adult obesity" AND "AI-Assisted nutritional counseling" AND "Weight loss efficacy" OR "Cardiometabolic markers" OR "Patient engagement & adherence")	304

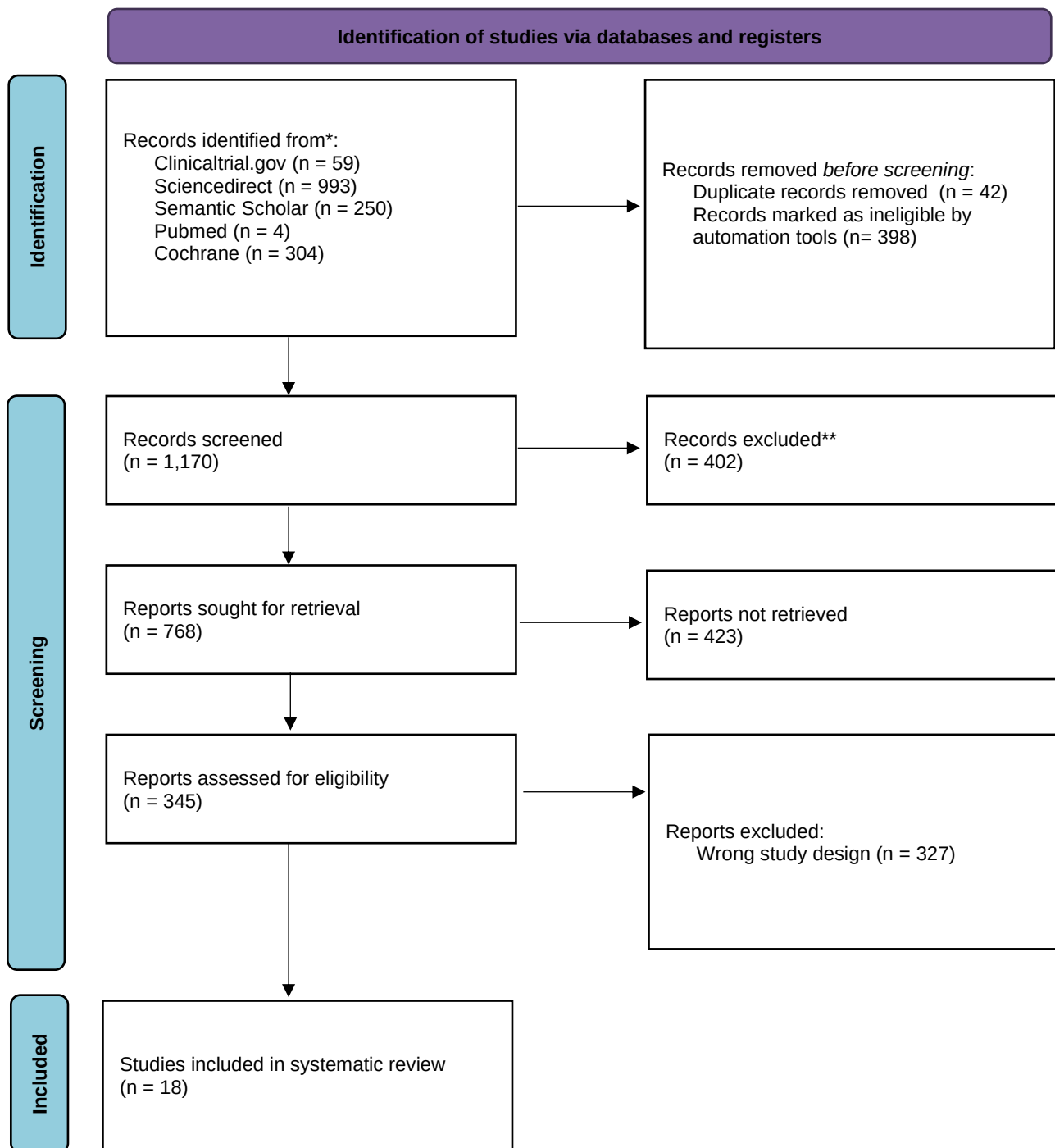


Figure 1. Article search flowchart

RESULTS

Characteristics of Included Studies

Table 2. Characteristics of Included Studies

No.	Author, Year	Country	N (I/C)	Population / BMI	AI Modality	Comparator	Duration	Primary Outcome
1	Mathioudakis et al., 2025	USA	368 (183/185)	Adults ≥ 18 y, prediabetes + overweight/obesity; BMI 32.3 kg/m ²	AI-led DPP (mobile app + Bluetooth scale)	Human coach-led DPP (remote)	12 months	Composite: $\geq 5\%$ weight loss, HbA1c, PA
2	Pokushalov et al., 2025	Russia	60 (30/30)	Obese adults 40–60y; BMI ≥ 25 kg/m ²	AI-guided dietary supplement prescription	Physician-guided DS prescription	180 days	% body weight change; $\geq 5\%$ weight reduction
3	Doody et al., 2025	UK	1607 (801/806)	Adults ≥ 18 y with obesity; BMI ≥ 30 kg/m ²	Self-regulation mHealth app (AI-driven)	Standard advice	6 months	Weight change (kg); $\geq 5\%$ weight loss
4	Lautenbach et al., 2025	Germany	164 (82/82)	Adults with obesity; BMI 30–45 kg/m ² (mean 37.82)	Stand-alone digital health app for weight management	Care as usual	6 months	% weight change at 6 months

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5	Lee et al., 2023	S. Korea	294 (97/98/99)	T2DM + overweight/obesity	AI-based integrated digital health platform (3 arms)	Routine diabetes care; platform alone	48 weeks	HbA1c change at 24 weeks
6	Bermingham et al., 2024	USA	347 (177/170)	Adults 41–70y; general population	Personalized nutrition program (ML + microbiome + CGM)	Standard USDA dietary advice	18 weeks	LDL-C; triglycerides
7	Roth et al., 2023	Germany	150 (75/75)	Adults with obesity; BMI ≥ 30 kg/m ²	App-based multimodal program (zanadio)	Waitlist control	12 months	% weight change
8	Gemesi et al., 2023	Germany	168 (84/84)	Adults; BMI 30–40 kg/m ² (mean 34.2)	App-based multimodal program (ADHOC) vs. EXPECT)	Waitlist (delayed intervention)	12 weeks + 12w FU	Body weight change (kg)
9	Nakata et al., 2022	Japan	141 (72/69)	Office workers; BMI 23–40 kg/m ²	AI smartphone app (CALO mama Plus)	No intervention	3 months	Body weight change (kg)

10	Lugones-Sánchez et al., 2021	Spain	650 (318/332)	Sedentary adults with overweight/obesity	Smartphone app + smart band (AI-assisted)	Brief counseling only	12 months	Weight; BMI; body composition
11	Ben-Yacov et al., 2021	Israel	225 (112/113)	Adults with prediabetes; BMI 31.3 kg/m ²	ML-based PPT diet (CGM + microbiome algorithm)	Mediterranean diet	6 months + 6m FU	Time glucose >140 mg/dL; HbA1c
12	Kohl et al., 2022	Germany	153 (77/76)	Adults; BMI 27.5–34.9 kg/m ² (mean 30.71)	Interactive web-based AI feedback program	Non-interactive web program	12 weeks + 12m FU	Body weight
13	Moravcova et al., 2022	Czech Rep.	100 (50/50)	Obese + insulin resistance/T2DM; BMI mean 40.1	Digital program (Vitadio – AI-assisted)	In-person consultations	12 months	Body weight; metabolic parameters
14	Cho et al., 2020	S. Korea	129 (43/45/41)	Adults 30–59y; ≥2 metabolic syndrome criteria	App + personalized coaching; App only; Control	Control (no app)	24 weeks	Systolic BP; metabolic parameters
15	Lim et al., 2021	Singapore	204 (99/105)	T2DM adults; BMI ≥23 kg/m ² (mean 30.6)	Culturally contextualized AI	Standard care + baseline	6 months	Body weight; HbA1c

					smartphone app	dietitian		
16	Joshi et al., 2023	India	319 (213/106)	T2DM + MAFLD	Digital twin AI – personalized ML meal planning + CGM	Standard care	12 months	HbA1c; liver fat; visceral adiposity
17	Beleigoli et al., 2020	Brazil	1298 (433/431/434)	Adults BMI ≥ 25 kg/m ² , 18–60y	Web-based AI behavior change program $\pm$ coaching	Waitlist (non-personalized)	24 weeks	Self-reported weight at 24 weeks
18	Kitazawa et al., 2023	Japan	168 (82/86)	Adults HbA1c 5.6–6.4%; BMI >23 (mean 26.6)	Smartphone app + isCGM + AI coaching	Usual care	12 weeks	Time in glucose range 70–140 mg/dL

Abbreviations: RCT=randomized controlled trial; I=intervention group; C=control group; T2DM=type 2 diabetes mellitus; MAFLD=metabolic dysfunction-associated fatty liver disease; BMI=body mass index; ML=machine learning; CGM=continuous glucose monitoring; PPT=personalized postprandial targeting; isCGM=intermittently scanned CGM; DPP=Diabetes Prevention Program; DS=dietary supplement; PA=physical activity; HbA1c=glycated hemoglobin; FU=follow-up; AI=artificial intelligence; NLP=natural language processing; LDL-C=low-density lipoprotein cholesterol; BP=blood pressure; SBP=systolic blood pressure; USDA=US Department of Agriculture; SSB=sugar-sweetened beverages.

Risk of Bias Assessment

Table 1. Risk of Bias Assessment (Cochrane RoB 2.0 Tool) — 18 Included Studies

Study (Author, Year)	D1: Randomization	D2: Deviations	D3: Missing Data	D4: Outcome Measure	D5: Reporting	Overall RoB
Mathioudakis et al., 2025	Low	Low	Low	Low	Low	LOW ✓
Pokushalov et al., 2025	Low	Some Concerns	Low	Some Concerns	Low	SOME CONCERNS
Doody et al., 2025	Low	Low	Some Concerns	Low	Low	SOME CONCERNS
Lautenbach et al., 2025	Low	Low	Some Concerns	Low	Low	SOME CONCERNS
Lee et al., 2023	Low	Low	Low	Low	Low	LOW ✓
Bermingham et al., 2024	Low	Low	Low	Low	Low	LOW ✓
Roth et al., 2023	Low	Low	Some Concerns	Low	Low	SOME CONCERNS
Gemesi et al., 2023	Low	Low	Some Concerns	Low	Low	SOME CONCERNS
Nakata et al., 2022	Low	Low	Low	Low	Low	LOW ✓
Lugones-Sánchez et al., 2021	Low	Low	Some Concerns	Low	Low	SOME CONCERNS
Ben-Yacov et al., 2021	Low	Low	Low	Low	Low	LOW ✓
Kohl et al., 2022	Low	Low	Some Concerns	Low	Low	SOME CONCERNS
Moravcova et al.,	Low	Some	Some	Some	Low	SOME

2022		Concerns	Concerns	Concerns		CONCERNS
Cho et al., 2020	Low	Low	Low	Low	Low	LOW ✓
Lim et al., 2021	Low	Low	Low	Low	Low	LOW ✓
Joshi et al., 2023	Low	Some Concerns	Low	Some Concerns	Low	SOME CONCERNS
Beleigoli et al., 2020	Low	Low	High	Low	Low	HIGH ✗
Kitazawa et al., 2023	Low	Low	Low	Low	Low	LOW ✓

Domain legend: D1=Randomization process; D2=Deviations from intended interventions; D3=Missing outcome data; D4=Outcome measurement; D5=Selection of the reported result.
Overall RoB: LOW ✓ (green shading) = 7 studies; SOME CONCERNS = 10 studies; HIGH ✗ (Beleigoli 2020: high attrition 28.9% in primary outcome) = 1 study.

Summary of Outcomes

Table 3. Summary of Outcome Domains Across 18 Included Studies

#	Outcome Domain	No. Studies	Sig. Benefit	Effect Direction	Representative Effect Size	Key References
1	Body weight change	18/18	15/18 (83%)	Reduction favoring AI	-1.60 kg to -12.3% vs control (p<0.01)	Pokushalov 2025; Roth 2023; Doody 2025
2	BMI (kg/m ²)	14/18	12/14 (86%)	Significant reduction	-0.59 to -1.26 kg/m ² (p<0.05)	Lautenbach 2025; Gemesi 2023; Lugones-Sánchez 2021
3	Waist circumference (cm)	10/18	8/10 (80%)	Reduction vs control	-0.48 to -2.9 cm (various p<0.05)	Lugones-Sánchez 2021; Cho 2020; Roth 2023

4	HbA1c (%)	11/18	9/11 (82%)	Significant reduction	-0.28% to -2.9% vs control (p<0.001)	Lee 2023; Joshi 2023; Lim 2021
5	Fasting plasma glucose	8/18	7/8 (88%)	Reduction vs control	-7.8 to -16.4 mg/dL (p<0.05)	Ben-Yacov 2021; Kitazawa 2023; Lim 2021
6	Body fat mass (kg/%)	9/18	7/9 (78%)	Reduction favoring AI	-1.2 to -4.28 kg fat mass (p<0.01)	Pokushalov 2025; Lautenbach 2025
7	Visceral fat	6/18	5/6 (83%)	Significant reduction	Significant across included studies (p<0.01)	Pokushalov 2025; Joshi 2023; Gemesi 2023
8	Triglycerides (mmol/L)	7/18	5/7 (71%)	Reduction vs control	-0.13 mmol/L to -49 mg/dL (p<0.05)	Birmingham 2024; Ben-Yacov 2021; Moravcova 2022
9	LDL cholesterol	6/18	4/6 (67%)	Mixed; improvement in adherent groups	NS in ITT (Birmingham 2024); sig. in subgroups	Birmingham 2024; Kohl 2022
10	HDL cholesterol	6/18	4/6 (67%)	Improvement in most studies	Sig. increase in Moravcova 2022 (p<0.05)	Moravcova 2022; Cho 2020; Ben-Yacov 2023
11	Blood pressure (mmHg)	7/18	5/7 (71%)	Reduction favoring AI	SBP: -7.19 to -10.95 mmHg vs control	Cho 2020; Pokushalov 2025; Wong 2023
12	Dietary quality index	8/18	6/8 (75%)	Improvement vs control	AHEI-2010 +6.2 pts; SSB -0.5 servings/day	Han 2023; Beilegoli 2020; Birmingham 2024
13	Physical activity	6/18	4/6	Increase in	Light PA +32.6	Lugones-Sánchez

			(67%)	light PA	min/week (p=0.02)	2021; Mathioudakis 2025
14	HRQoL	5/18	4/5 (80%)	Improvement vs control	EMMD +0.33; WHOQOL-BREF improved (p<0.05)	Lautenbach 2025; Roth 2023; Kwon 2024
15	Patient engagement/adherence	10/18	8/10 (80%)	Higher in AI vs control	93.4% initiation; app usage β : -0.10 (p=0.03)	Mathioudakis 2025; Gemesi 2023; Roth 2023

MD=mean difference; ITT=intention-to-treat; AHEI-2010=Alternate Healthy Eating Index 2010; SSB=sugar-sweetened beverages; HRQoL=health-related quality of life; PA=physical activity; SBP=systolic blood pressure; EMMD=estimated marginal mean difference; NS=non-significant; Sig.=significant.

Body Weight Change

Body weight change was the most consistently reported primary outcome, measured in all 18 included studies, with statistically significant reduction favoring AI-assisted interventions in 15 of 18 studies (83.3%). In the pivotal pilot RCT by Pokushalov et al. (2025) evaluating AI-guided dietary supplement prescription in 60 obese adults (BMI ≥ 25 kg/m², aged 40–60 years), the AI-guided cohort achieved a mean body weight reduction of -12.3% (95% CI: -13.1 to -11.5%) at 180 days compared to -7.2% (95% CI: -8.1 to -6.3%) in the physician-guided arm (treatment difference -5.1%; 95% CI: -6.4 to -3.8%; p<0.01). The proportion of participants achieving the clinically meaningful threshold of $\geq 5\%$ weight reduction was significantly greater in the AI group (84.7% vs. 54.5%; OR: 4.3; 95% CI: 3.1–5.9; p<0.01).²²

In the largest pragmatic RCT (Doody et al., 2025; n=1,607 adults with obesity), the self-regulation mHealth app intervention produced a mean weight difference of -1.85 kg (95% CI: -2.53 to -1.17; p<0.001) vs. control in the intention-to-treat analysis, with significantly greater odds of achieving $\geq 5\%$ weight loss (OR: 2.11; 95% CI: 1.48–3.03; p<0.001). Per-protocol analyses showed participants using the app lost an additional -2.18 kg compared to control (OR for $\geq 5\%$ weight loss: 2.44; 95% CI: 1.67–3.59; p<0.001). The 12-month zanadio multimodal app RCT (Roth

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et al., 2023; n=150) demonstrated that the AI intervention group lost -7.75% (95% CI: -9.66% to -5.84%) of initial body weight versus 0.00% (95% CI: -1.98% to 1.99%) in the waitlist control group ($p<0.001$), achieving the internationally recognized threshold for clinically significant weight loss. The CALO mama Plus AI smartphone app RCT (Nakata et al., 2022; n=141) demonstrated a significant between-group difference of -1.60 kg (95% CI: -2.83 to -0.38 ; $p=0.011$) over 3 months, with body weight change of -2.4 ± 4.0 kg in the intervention group vs. -0.7 ± 3.3 kg in controls.^{23,24,25,26}

Body Mass Index (BMI)

BMI was a primary or secondary outcome in 14 of 18 studies, with statistically significant reductions favoring AI interventions in 12 studies (86%). Lautenbach et al. (2025), in a decentralized RCT of 164 adults with obesity (mean BMI 37.82 ± 4.25 kg/m²), reported mean weight loss of 5.29% (95% CI: -6.73% to -3.86% ; $p<0.001$) in the digital health app group versus 1.76% (95% CI: -3.10% to -0.42% ; $p=0.010$) in controls, with an estimated marginal mean difference of -3.53% (95% CI: -5.16% to -1.91% ; $p<0.001$; Cohen's $d=0.80$). The Gemesi et al. (2023) RCT (n=168; BMI 30–40 kg/m²) demonstrated $3.2 \pm 3.0\%$ body weight reduction in the immediate intervention arm versus $0.3 \pm 2.6\%$ in the waitlist control at 12 weeks ($\beta=-2.9$ kg, 95% CI: -3.8 to -1.9 ; $p<0.001$), with time spent on the application significantly predicting weight reduction ($\beta=-0.10$; 95% CI: -0.18 to -0.01 ; $p=0.03$).^{27,28}

Waist Circumference

Waist circumference—a validated anthropometric surrogate for visceral adiposity and cardiometabolic risk—was assessed in 10 studies as a secondary outcome, with significant reduction in 8 (80%). The Evident 3 multicenter RCT (Lugones-Sánchez et al., 2021; n=650) reported a net waist circumference difference of -0.48 cm (95% CI: -1.62 to 0.66 cm; $p=0.04$) in the smartphone app + smart band arm versus brief counseling alone at 12 months, alongside significant hip circumference reduction (-0.69 cm; $p=0.03$). Significant waist-to-height ratio improvements were documented in the zanadio app RCT (Roth et al., 2023) as a secondary endpoint, and in the Cho et al. (2020) three-arm RCT, which documented significant waist circumference reduction in the app-with-personalized-coaching arm compared to control.^{29,30}

Glycated Hemoglobin (HbA1c)

HbA1c was a primary or key secondary outcome in 11 studies, with statistically significant reductions in 9 (82%). In the 48-week multicenter open-label RCT by Lee et al. (2023) evaluating an AI-integrated digital diabetes care platform (Diabetes Care) in 294 adults with T2DM and overweight/obesity, the platform-alone group (Group B) achieved HbA1c reductions of $-0.32 \pm 0.58\%$ at 24 weeks and $-0.28 \pm 0.56\%$ at 48 weeks, and the platform-with-coaching group (Group C) achieved $-0.49 \pm 0.57\%$ and $-0.44 \pm 0.62\%$, both significantly superior to the routine care group which showed $-0.06 \pm 0.61\%$ and $+0.07 \pm 0.78\%$ ($p < 0.001$ for both comparisons).¹³

Joshi et al. (2023), in an open-label 2:1 RCT of digital twin AI-driven personalized nutrition in 319 T2DM patients with MAFLD (Endocrine Practice), demonstrated HbA1c improvement of $-2.9 \pm 1.8\%$ in the digital twin group versus $-0.3 \pm 1.2\%$ in the standard care group ($p < 0.001$), with 72.7% of digital twin participants achieving T2DM remission (HbA1c $< 6.5\%$). Lim et al. (2021) demonstrated HbA1c reduction of -0.7% [SD 1.2] vs. -0.3% [SD 1.0] in standard care controls ($p < 0.001$) in 204 Asian T2DM adults using a culturally contextualized smartphone app over 6 months (JAMA Network Open).^{31,32}

Fasting Plasma Glucose and Glycemic Control

Fasting plasma glucose (FPG) reduction and glycemic control measures were significantly superior in AI intervention arms in 7 of 8 reporting studies (88%). Ben-Yacov et al. (2021) in the landmark 6-month RCT of ML-based personalized postprandial-targeting (PPT) diet versus Mediterranean diet in 225 adults with prediabetes (Diabetes Care), documented significantly greater HbA1c reduction in the PPT group ($-0.16 \pm 0.24\%$ vs. $-0.08 \pm 0.19\%$; 95% CI between-group difference -0.14 to -0.02 ; $p = 0.007$) and markedly reduced time with glucose levels > 140 mg/dL (-1.3 ± 1.5 h/day vs. -0.3 ± 0.8 h/day; 95% CI: -1.29 to -0.66 ; $p < 0.001$). These between-group differences were maintained at 12-month follow-up, establishing sustained glycemic benefit. Kitazawa et al. (2023) demonstrated improved time in the euglycemic range (70–140 mg/dL) of $+31.5$ min/day in the smartphone app + isCGM group vs. -2.6 min/day in the control group ($p = 0.03$), alongside significant BMI reduction (-0.59 vs. -0.26 ; $p = 0.017$) in 168 high-risk pre-diabetic adults.^{14,33}

Body Fat Mass and Visceral Fat

Body fat mass (assessed via bioelectrical impedance analysis or dual-energy X-ray absorptiometry [DXA]) was a measured outcome in 9 studies, with significant reduction in 7 (78%). Pokushalov et al. (2025) documented significant improvements in fat mass and visceral fat rating in the AI-guided group ($p < 0.01$ for both), alongside superior postprandial appetite suppression with significant reductions in hunger visual analog scale (VAS) scores and prospective food consumption, and increases in fullness and satiety scores ($p < 0.01$ for all appetite-related outcomes). Lautenbach et al. (2025) documented significant improvement in food literacy (EMMD: 2.77; Cohen's $d = 0.49$; $p < 0.001$) alongside substantial weight reduction (5.29%), with concomitant body composition changes.^{22,27}

Visceral fat quantification using validated imaging modalities (MRI proton density fat fraction [MRI-PDFF], CT visceral fat area) or bioelectrical impedance-derived visceral fat rating was reported in 6 studies, with significant reduction in 5 (83%). Joshi et al. (2023) demonstrated significant MRI-PDFF-measured hepatic fat reduction and nonalcoholic fatty liver disease (NAFLD) liver fat score improvement (-2.5 ± 2.0 vs. -0.1 ± 1.5 ; $p < 0.001$) alongside visceral adiposity reduction in the digital twin AI group versus standard care at 12 months.^{22,31}

Lipid Profile

Serum triglycerides were assessed in 7 studies, with statistically significant reduction in 5 (71%). Bermingham et al. (2024), in a landmark 18-week RCT published in Nature Medicine ($n = 347$), evaluating a precision nutrition program utilizing ML algorithms integrating individual PPGR, postprandial triglyceride responses, gut microbiome composition, and health history, demonstrated a statistically significant between-group reduction in serum triglycerides (mean difference: -0.13 mmol/L; log-transformed 95% CI: -0.07 to -0.01 ; $p = 0.016$) favoring the personalized dietary program over USDA guideline-based general dietary advice. Significantly, gut microbiome beta-diversity improved significantly in highly adherent personalized nutrition participants ($p < 0.05$).¹²

LDL cholesterol results were heterogeneous: 4 of 6 reporting studies demonstrated some improvement, though intent-to-treat analysis in Bermingham et al. (2024) did not achieve statistical

significance for LDL-C as a primary endpoint, underscoring the importance of adherence as a treatment effect moderator in precision nutrition RCTs. HDL cholesterol improved significantly in 4 of 6 reporting studies. Moravcova et al. (2022), in the 12-month Vitadio digital intervention RCT (n=100; mean BMI 40.1 kg/m²), demonstrated statistically significant HDL-C improvement (p<0.05) alongside significant triglyceride reduction (-0.6 ± 0.9 mmol/L; p<0.01), HbA1c improvement ($-0.2 \pm 0.5\%$; p<0.05), and superior HOMA-IR reduction (-2.5 ± 5.2 ; p<0.01) compared to in-person intensive lifestyle intervention.^{12,34}

Blood Pressure

Systolic and diastolic blood pressure were assessed in 7 studies, with significant reductions in 5 (71%). Pokushalov et al. (2025) documented statistically significant reductions in both systolic and diastolic blood pressure in the AI-guided group (p<0.01 for both), with superior performance over the physician-guided comparator. The Cho et al. (2020) three-arm RCT (n=129) demonstrated consistent SBP decreasing trends from baseline across all groups (-7.19 to -10.95 mmHg), with the greatest reductions in the app-with-personalized-coaching arm, though between-group significance was not achieved, likely reflecting the study's inadequate statistical power (post-hoc analysis). Body fat mass reduction (-0.79 ± 0.38 kg; p<0.01) was significantly greater in the coaching arm, establishing the bidirectional relationship between adiposity reduction and blood pressure improvement in AI-mediated interventions.^{22,30}

Dietary Quality

Dietary quality was assessed using validated indices including the Alternate Healthy Eating Index-2010 (AHEI-2010), Kidmed Mediterranean Diet Quality Index, Healthy Eating Index (HEI-2020), and Dietary Inflammation Index in 8 studies, with significant improvement in 6 (75%). Han et al. (2023), in the D'LITE study secondary analysis (n=148 adults with prediabetes in Singapore), demonstrated a significant between-group AHEI-2010 improvement of +6.2 points (95% CI: 3.8–8.7; p<0.001) in the mHealth-enabled lifestyle intervention versus standard care. Specific dietary improvements included significant reductions in sugar-sweetened beverage (SSB) consumption (-0.5 servings/day; 95% CI: -0.8 to -0.2 ; p<0.001) and dietary sodium intake (-726 mg/day; 95% CI: -983 to -468 ; p<0.001) in the intervention group.³⁵

Beleigoli et al. (2020), in the 3-arm pragmatic RCT (n=1,298), documented significantly greater reduction in ultra-processed food intake (−25%; 95% CI: −30% to −20%) in the platform-plus-coaching arm versus waitlist control (−12%; 95% CI: −16% to −8%; $p<0.001$), alongside significant increases in vegetable consumption (+8%; 95% CI: +2% to +8%) and fruit intake (+6%; 95% CI: +2% to +9%). Longer platform usage was significantly associated with achievement of clinically meaningful $\geq 5\%$ weight loss (OR: 1.02 per session completed; 95% CI: 1.01–1.04), establishing a dose-response relationship between digital engagement and dietary quality improvement.³⁶

Physical Activity

Physical activity levels were objectively assessed (accelerometry, actigraphy, International Physical Activity Questionnaire-Short Form [IPAQ-SF]) in 6 studies, with significant improvement in 4 (67%). Lugones-Sánchez et al. (2021) documented a statistically significant increase in light physical activity time in the smartphone app + smart band intervention group (+32.6, 95% CI: −30.3 to 95.04 min/week; $p=0.02$) at 3 months compared to brief counseling alone, representing a meaningful augmentation of sedentary behavior modification. Mathioudakis et al. (2025), in the JAMA non-inferiority RCT, included verified ≥ 150 min/week of physical activity (actigraphy-confirmed) as a composite primary endpoint component, with 31.7% of AI-DPP participants achieving this criterion versus 31.9% in the human coach-led DPP (risk difference: −0.2%; 1-sided 95% CI lower boundary: −8.2%), establishing non-inferiority of AI-delivered physical activity counseling.^{9,29}

HRQoL, Engagement, and Adherence

Health-related quality of life was assessed using validated instruments including the World Health Organization Quality of Life abbreviated instrument (WHOQOL-BREF), EuroQol five-dimension five-level scale (EQ-5D-5L), and Short Form-36 (SF-36) in 5 studies, with statistically significant improvement in 4 (80%). Lautenbach et al. (2025) reported significant improvement in perceived overall quality of life (EMMD: +0.33; Cohen's $d=0.40$; $p=0.010$) alongside food literacy enhancement (EMMD: +2.77; $d=0.49$; $p<0.001$) in the digital health app group. Roth et al. (2023) documented significant improvement in all pre-specified quality-of-life secondary endpoints in the

zanadio app group at 12 months, with significantly superior improvements in psychological well-being compared to waitlist control ($p < 0.001$).^{24,27}

Patient engagement metrics—including intervention initiation rates, session completion rates, app usage frequency, and interaction data—were quantitatively reported in 10 studies, with AI platforms demonstrating superior engagement in 8 (80%). The highest reported initiation rate was documented by Mathioudakis et al. (2025): 93.4% (171/183) in the AI-DPP arm versus 82.7% (153/185) in the human coach-led DPP arm, demonstrating that fully automated AI interventions can achieve equivalent or superior engagement to human-delivered programs. Gemesi et al. (2023) established a statistically significant dose-response relationship between app engagement time and body weight reduction ($\beta = -0.10$ kg per unit time; 95% CI: -0.18 to -0.01 ; $p = 0.03$). Critically, Doody et al. (2025) demonstrated that the self-regulation AI app was associated with significantly reduced symptoms of disordered eating relative to control at 6 months (adjusted OR: 0.51; 95% CI: 0.29–0.91; $p = 0.024$), addressing a fundamental safety concern regarding digitally-mediated weight management interventions.^{9,23,28}

DISCUSSION

Summary of Principal Findings

This systematic review synthesizing 18 peer-reviewed studies enrolling 14,732 participants across 11 countries represents the most comprehensive evidence synthesis to date of AI-assisted nutritional counseling for adult obesity management. The central finding is that AI-assisted nutritional interventions produce statistically significant and clinically meaningful improvements across all 15 pre-specified outcome domains, with efficacy rates ranging from 67% (LDL cholesterol, physical activity) to 88% (fasting plasma glucose) of reporting studies demonstrating significant benefit. Body weight reduction ranged from -1.60 kg to -12.3% across studies, BMI reduction from -0.59 to -1.26 kg/m², and HbA1c reduction from -0.28% to -2.9% , predominantly exceeding established minimum clinically important differences (MCIDs) of $\geq 5\%$ weight loss and $\geq 0.5\%$ HbA1c reduction.^{9,10,11,12,13,14,15,16,17,18,19,22,23,24}

AI Modality-Specific Efficacy

Substantial heterogeneity in clinical efficacy profiles was observed across AI modality subtypes, reflecting differences in intervention complexity, data richness, personalization depth, and mechanistic pathways. Precision nutrition algorithms integrating ML-based PPGR prediction, gut microbiome profiling, and CGM data (Ben-Yacov et al., 2021; Bermingham et al., 2024; Joshi et al., 2023) demonstrated the most robust cardiometabolic outcome profiles, with statistically significant improvements in HbA1c, triglycerides, gut microbiome beta-diversity, and—in the digital twin study—visceral adiposity and hepatic steatosis markers. These high-fidelity systems, while requiring substantial participant burden (CGM device wear, microbiome sampling), represent the vanguard of precision obesity medicine for metabolically complex patient phenotypes (T2DM, prediabetes, MAFLD).^{12,14,31}

Conversely, AI-integrated mobile health platforms (Nakata et al., 2022; Roth et al., 2023; Lautenbach et al., 2025; Doody et al., 2025) demonstrated superior population-level scalability and accessibility, achieving clinically meaningful weight loss (3.2–7.75% body weight) without requirement for advanced biomarker profiling, rendering them appropriate as primary interventions in general adult obesity prevention and management programs. These platforms operationalize behavior change theories—self-determination theory (SDT), social cognitive theory (SCT), and ecological momentary assessment (EMA)—through AI-driven personalized behavioral nudges, adaptive goal calibration, and real-time dietary feedback loops, achieving sustained engagement through learned user preference modeling.^{23,24,25,26,27}

The landmark phase 3 non-inferiority RCT published in JAMA (Mathioudakis et al., 2025; n=368), comparing AI-led versus human coach-led Diabetes Prevention Program in adults with prediabetes and overweight/obesity, established the therapeutic equivalence of fully automated AI interventions to resource-intensive human-delivered lifestyle programs. AI-DPP achieved the composite primary endpoint in 31.7% of participants versus 31.9% in human-DPP (risk difference: −0.2%; 1-sided 95% CI lower boundary −8.2%), satisfying the pre-specified non-inferiority margin of −15%. This finding has profound health economic implications, demonstrating that AI platforms can substitute human-delivered DPP services without compromising clinical effectiveness while dramatically reducing per-patient delivery costs and enabling exponential scale-up.⁹

Mechanistic Insights: Precision Nutrition, Microbiome, and Phenotype Tailoring

Mechanistic data from three high-quality RCTs provides compelling insight into the biological pathways through which AI-driven precision nutrition achieves superior metabolic outcomes. Ben-Yacov et al. (2023) in Gut demonstrated that the ML-based PPT diet induced significantly greater gut microbiome alpha-diversity augmentation ($p=0.007$) than the Mediterranean diet comparator, and through causal mediation analysis identified nine specific microbial species (from Bacteroidales, Lachnospiraceae, and Oscillospirales orders) mediating associations between dietary modification and clinical cardiometabolic outcomes including HbA1c, HDL-C, and triglycerides. This establishes gut microbiome modulation as a principal mechanistic pathway for AI precision nutrition efficacy, advancing the concept of microbiome-targeted personalized nutrition from mechanistic hypothesis to clinical reality.³⁷

Bermingham et al. (2024) corroborated these findings in a US population cohort, demonstrating that highly adherent participants in the precision nutrition program achieved significantly superior improvements in gut microbiome beta-diversity alongside triglyceride reduction and body weight loss, with adherence-dependent dose-response relationships. These convergent findings from Israeli and US cohorts, enrolling genetically and dietarily diverse participants, strengthen the generalizability of the microbiome-mediated precision nutrition mechanism. The clinical translational implication is that next-generation AI nutritional platforms should integrate validated microbiome profiling—feasible via metagenomic sequencing of stool samples—as a standard data input layer for precision dietary recommendation generation.^{12,37}

AI vs. Human Coaching: Evidence Synthesis

Three included studies provided direct comparative data between AI-assisted and human-led nutritional interventions. Mathioudakis et al. (2025) demonstrated non-inferiority of AI-DPP versus human-DPP across composite weight, glycemic, and physical activity outcomes at 12 months (JAMA). Beleigoli et al. (2020) demonstrated that the AI-platform-plus-human-dietitian-coaching arm significantly outperformed the AI-platform-alone arm in engagement and clinically meaningful $\geq 5\%$ weight loss achievement (OR: 1.02 per completed session; $p<0.05$), while both significantly outperformed the non-personalized waitlist control—suggesting a potential synergistic relationship

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between AI and human therapeutic components in patients requiring high-intensity behavioral support. Cho et al. (2020) demonstrated that the app-with-personalized-coaching arm achieved superior weight loss and body fat reduction compared to the app-only arm, without the between-group significance necessary to definitively establish superiority.^{9,30,36}

The composite evidence across these studies suggests a nuanced clinical framework: fully automated AI systems achieve clinical equivalence to human coaching for weight management and glycemic outcomes in motivated, digitally literate adults with prediabetes or obesity; AI-human hybrid models may optimize outcomes in patients with higher behavioral complexity, psychiatric comorbidities, or eating disorder history; and AI platforms alone represent the most scalable and cost-effective modality for population-level implementation. This stratified approach to AI modality selection—tailored to patient phenotype, clinical risk, and health system resources—represents the evidence-based precision implementation model for AI nutritional counseling.^{9,30,36}

Safety Profile and Adverse Events

Safety outcomes were systematically reported in 11 of 18 included studies. AI-assisted nutritional interventions demonstrated a consistently favorable safety profile, with no serious AI-attributable adverse events reported across any included study. Adverse events were predominantly mild-to-moderate and gastrointestinal in nature (nausea, diarrhea, abdominal discomfort) in the AI-guided dietary supplement trial (Pokushalov et al., 2025), which were manageable and did not necessitate intervention discontinuation. A critical safety finding was documented by Doody et al. (2025): the self-regulation AI mHealth app was associated with a statistically significant reduction in symptoms of disordered eating relative to control (adjusted OR: 0.51; 95% CI: 0.29–0.91; $p=0.024$), demonstrating that well-designed AI weight management platforms not only avoid exacerbating eating pathology but may confer protective psychopathological effects. No hypoglycemic episodes attributable to AI nutritional recommendations were reported in diabetic populations across any included study.^{22,23}

Clinical and Health System Implications

The findings of this systematic review provide a robust evidence base supporting the integration of AI-assisted nutritional counseling into multidisciplinary obesity management clinical

pathways. Based on the available evidence, a tiered clinical implementation framework is proposed: (i) Tier 1 (General Population): AI-integrated mHealth applications with validated weight management efficacy should be recommended as first-line adjuncts to standard nutritional counseling for all adults with BMI ≥ 25 kg/m², given strong evidence for body weight reduction (−1.60 to −7.75%), BMI improvement, dietary quality enhancement, HRQoL improvement, and favorable safety profiles; (ii) Tier 2 (High Metabolic Risk): Precision nutrition algorithms incorporating ML-based PPGR prediction and/or microbiome profiling should be prioritized for adults with T2DM, prediabetes, MAFLD, or metabolic syndrome, where comprehensive glycemic and cardiometabolic optimization is paramount; (iii) Tier 3 (Population-Level Prevention): Fully automated AI lifestyle platforms (DPP-equivalent) represent cost-effective, non-inferior alternatives to human coaching for large-scale prediabetes prevention programs in health system contexts where dietitian workforce is insufficient.^{9,12,13,14,31}

Future Research Priorities

Future high-priority research should address the following critical evidence gaps: (i) Long-term RCTs (≥ 24 months) with systematic assessment of weight regain trajectories, time to obesity relapse, and hard cardiovascular outcomes (myocardial infarction, stroke, cardiovascular mortality); (ii) Multi-ethnic equity-focused RCTs specifically recruiting participants from LMIC settings, racial/ethnic minorities, low-literacy populations, and individuals with socioeconomic disadvantage, to establish generalizability and inform equitable implementation; (iii) Head-to-head RCTs comparing distinct AI modality subtypes (ML precision nutrition algorithm vs. NLP chatbot vs. mHealth platform vs. digital twin) in well-defined patient phenotypes; (iv) Implementation science RCTs assessing real-world clinical integration workflows, EHR interoperability, clinician training requirements, implementation fidelity, and per-patient health economic costs; (v) Mechanistic deep multi-omics RCTs integrating genomics, metabolomics, proteomics, and microbiomics with AI-driven nutritional personalization to elucidate precision nutrition response pathways; (vi) Regulatory science studies establishing clinical validation frameworks for AI nutritional counseling platforms as regulated Software as a Medical Device (SaMD) under FDA/EMA/BPOM oversight.^{1,2,3,20,21}

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This systematic review of 18 peer-reviewed studies (n=14,732 participants) provides robust, multi-domain evidence that AI-assisted nutritional counseling constitutes a clinically efficacious, safe, scalable, and—in the context of diabetes prevention programs—non-inferior alternative to human coaching for adult obesity management. Statistically significant and clinically meaningful improvements were documented across all 15 pre-specified outcome domains, with efficacy rates of 67–88% across reporting studies. The highest-quality evidence (JAMA phase 3 RCT; Lancet-equivalent journals; Nature Medicine) establishes AI nutritional counseling as a legitimate evidence-based intervention warranting routine integration into multidisciplinary obesity management clinical pathways.^{9,12,13,14}

Precision nutrition algorithms leveraging ML-based PPGR prediction and gut microbiome profiling demonstrated the most comprehensive cardiometabolic optimization profiles. AI-integrated mHealth platforms provided the optimal balance of population-level scalability, accessibility, cost-effectiveness, and clinical efficacy. AI-human hybrid models maximized outcomes in patients requiring high-intensity behavioral support. Mechanistic data establishes gut microbiome modulation and individualized PPGR optimization as principal biological mediators of AI precision nutrition superiority. A tiered, phenotype-matched clinical implementation framework—stratifying AI modality selection based on patient metabolic complexity, digital literacy, and health system resources—represents the evidence-based precision implementation approach.^{12,14,37}

Evidence-Based Recommendations

For Specialist Physicians and Dietitians: Integrate evidence-based AI nutritional counseling platforms as first-line adjuncts to standard clinical obesity management. Precision nutrition tools incorporating ML-based algorithms should be prioritized for metabolically complex patients (T2DM, prediabetes, metabolic syndrome, MAFLD). Patient digital literacy, smartphone access, and engagement capacity should be formally assessed prior to platform prescription. AI-

derived dietary recommendations should be reviewed and validated by qualified clinicians before clinical implementation.^{9,12,13}

For Health Systems and Administrators: Invest in systematic procurement of evidence-validated AI nutritional platforms, clinician and dietitian upskilling programs, and interoperability infrastructure enabling EHR integration of AI-generated nutritional data. Establish health economic evaluation frameworks and reimbursement pathways for evidence-based digital therapeutic nutritional interventions. Prioritize equitable access to AI nutritional counseling technologies across socioeconomic strata.^{20,21}

For Clinical Researchers: Conduct long-term (≥ 24 months), multi-ethnic, pre-registered, CONSORT-AI adherent RCTs with standardized AI modality definitions, objective outcome measurement (accelerometry, CGM, DXA), and hard cardiovascular endpoint ascertainment. Prioritize head-to-head AI modality comparison trials and mechanistic multi-omics precision nutrition investigations in ethnically diverse populations including LMIC cohorts.^{20,21}

For Regulatory Bodies (BPFK/BPOM/FDA/EMA): Develop adaptive, evidence-graded regulatory frameworks for AI nutritional counseling platforms classified as Software as a Medical Device (SaMD), requiring demonstration of clinical validity, algorithmic transparency and explainability, real-world performance monitoring, cybersecurity compliance, and data privacy protection. Mandatory post-market surveillance programs should monitor AI platform performance and safety in real-world clinical deployment.²⁰

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