Current Cardiovascular Risk Reports (2025) 19:24
https://doi.org/10.1007/s12170-025-00776-7

REVIEW

Harnessing Artificial Intelligence for Obesity Care: A Systematic Review of AI-Enabled Behavioral Coaching Platforms, Outcomes, and Ethical Implications

Rajiev Hallock[1,2] · Nihit Mehta[2] · Niki Patel[1,2] · Niteesh Ganesan[2] · Christine Kang[2] · Melissa Pulis[2] · Johnie Rose[2]

Received: 9 June 2025 / Accepted: 20 August 2025

Abstract

Purpose of Review Artificial intelligence (AI) enabled behavioral health coaching has emerged as a potential solution for managing obesity and related complications. This review aims to evaluate the effectiveness, engagement, and ethical implications of AI-enabled behavioral coaching platforms in the management of obesity.

Recent Findings Our search identified 21 relevant studies. Of these, 8 were randomized controlled trials and 13 were observational studies (including pretest-protest, longitudinal, retrospective cohort and single-arm intervention studies). AI-based platforms were associated with clinically significant weight loss (ranging from −0.8 kg to −13.9% of baseline weight), systolic blood pressure reductions up to −18.6 mmHg, improvements in HbA1c (up to −1.2% points) and LDL cholesterol (up to −66.6 mg/dL). Engagement levels were high, with retention rates ranging from 57 to 92%, particularly in hybrid models combining AI with human coaching. Ethical concerns reported included algorithmic opacity, lack of cultural tailoring, and unequal access due to technological barriers.

Summary AI-driven behavioral coaching platforms demonstrate promising effectiveness in obesity and cardiometabolic risk management, with outcomes comparable to traditional lifestyle interventions. However, ethical limitations, short study durations, and variability in design highlight the need for longer-term, diverse, and ethically grounded research. Future studies should emphasize algorithm transparency, data governance, equitable access, and integration into routine clinical care.

Keywords Artificial intelligence · Obesity · Behavioral health coaching · Cardiovascular risk · Diabetes · Digital health · Ethics

Introduction

Limited access to trained professionals often undermines the effectiveness of obesity care. Artificial Intelligence (AI) has been proposed as a strategy to overcome this barrier.

AI-enabled behavioral coaching delivers real-time, personalized support for health behavior change. Unlike static electronic tools, AI platforms adapt to user behavior, learn from ongoing data input, and provide feedback that improves through iterations. These systems have been integrated into mobile apps, wearable devices, and web-based platforms to deliver lifestyle interventions for weight management.

A growing body of research has begun to evaluate the feasibility, engagement, and effectiveness of AI-based coaching platforms. These include *conversational agents*, *just-in-time adaptive interventions (JITAI), digital twins,* and *predictive analytics frameworks* [1]. Platforms such as SureMediks, Lark, CALO mama Plus, Greenhabit Mobile, Endorse, Digital Twin, Paola, Shae mHealth, Hello Heart, PROTEIN, Redicare, and CoachAI represent

✉ Rajiev Hallock
hallocr@ccf.org; rkh47@case.edu

1 Enterprise Obesity Center, Cleveland Clinic Foundation, 9500 Euclid Ave. F20, Cleveland, OH 44195, USA

2 Department of Family Medicine and Community Health, Case Western Reserve University/University Hospitals Cleveland Medical Center, 11100 Euclid Ave. Bolwell Ste. 1200, Cleveland, OH 44106, United States

Published online: 01 October 2025

varied models of AI application in obesity care. These represent varied models of AI application in obesity care, ranging from structured programs for diabetes prevention to open-ended lifestyle coaching systems [1–23]. Many of these platforms integrate core behavioral strategies such as goal setting, self-monitoring, and accountability into AI-driven models.

The current landscape of AI-enabled behavioral coaching in obesity remains diverse, with variations in intervention design, target populations, outcomes assessed, and study quality. We review evidence about AI-powered coaching interventions for obesity and adiposity related sequelae, evaluating their components, reported outcomes, and limitations.

Artificial intelligence enabled behavioral coaching (AIBC) can serve as a clinician aid in obesity management and has advantages when compared to its in-person counterparts (currently the gold standard in obesity medicine). These novel platforms offer a scalable solution, addressing the growing need for lifestyle related coaching. AIBC systems use algorithmic agents to provide lifestyle recommendations, monitor progress, and provide feedback. While AI applications offer significant advantages of scalability, cost and convenience, their guidance and approach can often mirror that of human coaches, and can be indistinguishable from those provided by human behavioral coaching.

This scalability is especially crucial in underserved communities, both in the United States and abroad where access to behavioral therapists or health coaches is often limited. These underserved communities often face significant barriers to health care, including long travel distances, high out-of-pocket costs, and a shortage of trained professionals. Accessibility to AIBC's creates an opportunity to overcome these obstacles and provide evidence-based, practical, and affordable methods to deliver high-quality behavioral coaching and feedback in settings where access to such care is limited.

Methods

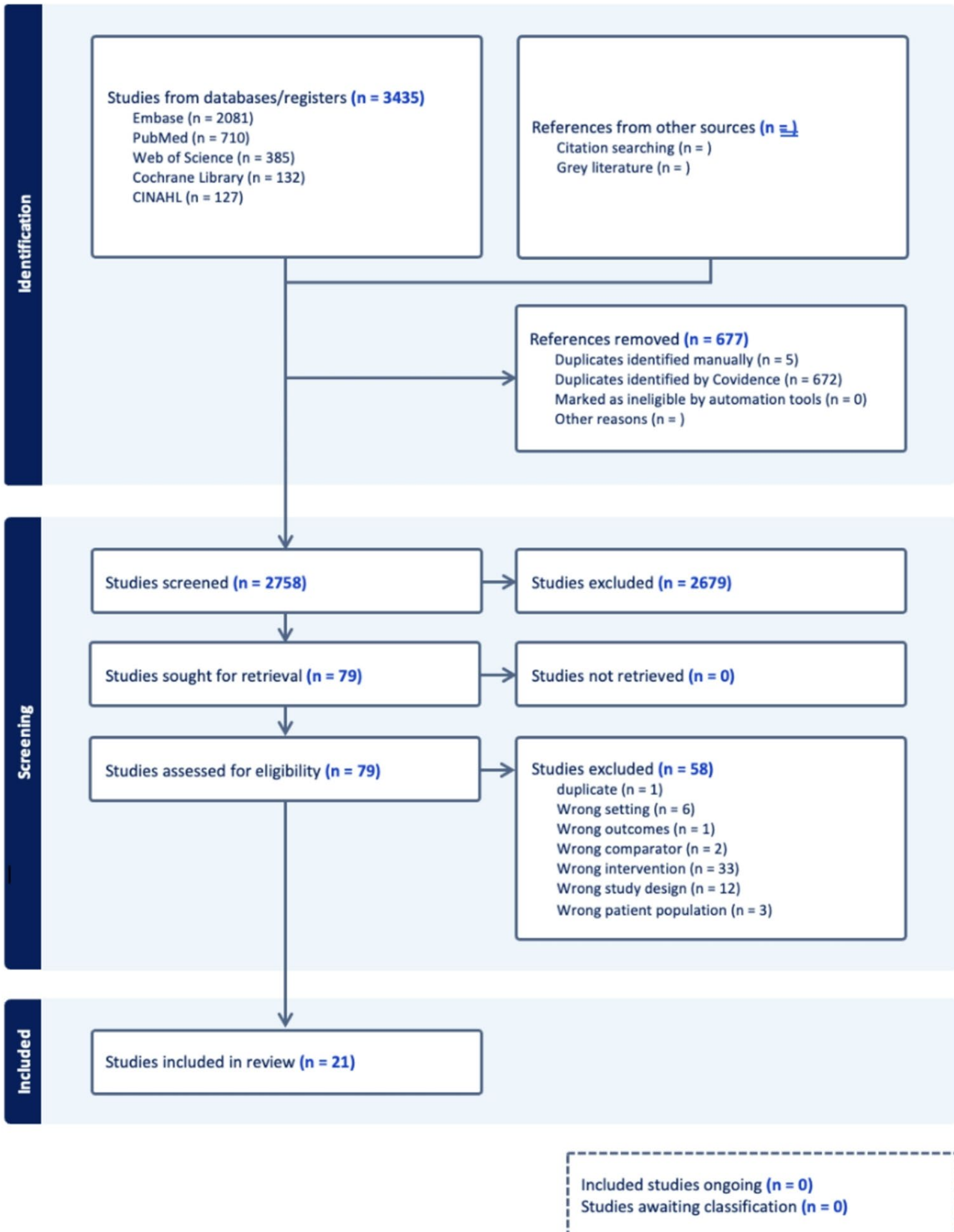
This systematic review was registered with PROSPERO conducted in accordance with PRISMA guidelines. A comprehensive search of PubMed, CINAHL, Cochrane Library, and Web of Science was performed from database inception through April 30, 2025. We initiated this review by developing a targeted set of search terms using keywords grouped into 4 domains; (1) health coaching, (2) obesity, (3) cardiovascular health, and (4) AI. Articles that included at least four terms spanning these domains, for example, "coaching," "behavioral change," "BMI," "blood pressure," and "machine learning", were deemed highly relevant. Articles with fewer than four terms underwent closer scrutiny for thematic alignment.

Two independent reviewers screened all titles and abstracts, followed by full-text review of eligible studies. Discrepancies were resolved by a third reviewer and thus consensus. Studies were included if they: (1) evaluated an AI-driven or AI-supported behavioral intervention; (2) targeted weight management or obesity-related outcomes; and (3) reported quantitative results. Exclusion criteria included non-empirical articles, editorials, reviews, and studies not isolating AI as the primary component of the intervention.

A total of 3,435 records were identified through electronic database searches: Embase ($n=2{,}081$), PubMed ($n=710$), Web of Science ($n=385$), Cochrane Library ($n=132$), and CINAHL ($n=127$). After removing 677 duplicates—672 through Covidence and 5 manually—2,758 unique records remained for title and abstract screening. Of these, 2,679 records were excluded based on.

relevance to the inclusion criteria. The remaining 79 full-text articles were assessed for eligibility. Following full-text review, 58 articles were excluded for reasons including wrong intervention ($n=33$), wrong study design ($n=12$), wrong setting ($n=6$), wrong patient population ($n=3$), duplicate ($n=1$), wrong outcomes ($n=1$), and wrong comparator ($n=2$). No articles were excluded due to retrieval issues.

Ultimately, 21 studies published between 2017 and 2025 met eligibility criteria, encompassing 8 RCTs and 13 observational studies including pretest-protest, longitudinal, retrospective cohort and single-arm intervention studies. Sample sizes ranged from 31 to 102,475 participants with follow-up between 4 weeks and 13 months. Twelve studies focused on adults classified as having overweight or obese (defined by BMI ≥ 25), 6 targeted Type 2 Diabetes Mellitus or pre-diabetes, 3 enrolled children/adolescents, however only 1 targeted a population of only children/adolescents, and 1 recruited community-dwelling older adults. Interventions employed conversational agents ($m=10$), just-in-time adaptive nudges ($n=5$), hybrid human-AI escalation ($n=3$) or a combination of interventions ($n=3$).



Results

The reviewed studies demonstrated a wide- array of AIBC platforms, including conversational agents, just in time adaptive interventions, digital twins and hybrid models. Despite differences in form and delivery, these platforms share core functionalities, delivering structured behavioral interventions, analyzing user generated data (e.g., physical activity, diet, sleep), and providing tailored feedback. Most were integrated into mobile apps or wearable devices, aiming to enhance motivation, engagement and sustained behavior change. Common behavioral techniques used across platforms included goal-setting, self-monitoring, feedback loops and gamification. The subsequent results are organized by health outcomes and subcategorized into study type.

Engagement and Adherence

Engagement and adherence were key metrics evaluated across nearly all included studies and serve as critical indicators of the feasibility, scalability, and acceptability of AI-based behavioral coaching interventions. Retention rates and frequency of interaction with digital tools varied by platform type, intensity, and user population.

In the PROTEIN (gamified nutrition) app RCT, Petra et al. (2024) found that 57% of users were still active at one year, highlighting long-term adherence in a general wellness context [6].

Among observational studies, Stein et al. [2], who implemented a fully automated conversational AI coach, reported that 62% of participants remained actively engaged after 6 months, with an average of 3.1 to 4.5 logins per week in an observational study [2]. Meanwhile, Graham et al. [9] observed a clear association between higher frequency of self-monitoring (e.g., weigh-ins) and greater weight loss over a 1 year retrospective longitudinal study. Supporting results of previously established relationships between self-monitoring and weight loss [24]. Participants who engaged daily with the AI coach were significantly more likely to achieve clinically meaningful outcomes, demonstrating that sustained interaction amplifies effectiveness [9, 24].

Further, Khokhar et al. [1, 20] reported exceptionally high engagement, supported by weekly weight logs and app activity. In the 2024 cohort, the platform demonstrated near-universal usage, with >90% of participants meeting minimum adherence benchmarks through 26 weeks [1, 20]. Lockwood et al. [21] also observed high adherence, with over 70% of participants achieving sustained interaction thresholds and consistent logging behaviors [16].

Collectively, these findings support the feasibility of deploying AI-based health interventions at scale, with engagement outcomes that compare favorably to traditional in-person programs. Importantly, adherence appeared to be enhanced when programs integrated multimodal feedback, gamification, or limited human support, allowing for flexible and sustained user participation.

Weight Outcomes

Of the included studies, 6 were randomized control trials, and 8 were observational in design. All but one study reported statistically significant weight reduction from baseline, with several demonstrating clinically meaningful effects.

Among the RCTs, a 12-month trial conducted by Joshi et al. [17] compared a digital twin coaching system to standard care, showing robust result, with 73.8% of the intervention group participants achieved > 5% body weight loss (BWL), and 41.6% achieved > 10% BWL, Statistically significant differences were observed in mean weight change (−7.4 kg vs. −0.4 kg; $p<0.001$), BMI reduction (−2.7 vs-0.1; $p<0.001$) and waist circumference reduction (−9.5 cm vs. 1.2 cm; $p<0.001$) [17]. Shamanna et al. [5] also reported significant improvements in the intervention group at 1 year compared to controls: with mean weight change of −5.2 kg versus −1.1 kg ($p<0.0001$) and BMI reduction of −2.3 kg/m² versus −0.4 kg/m² ($p<0.0001$) [5]

Nakata et al. (2022) evaluated a 3-month AI-assisted lifestyle intervention, observing a mean weight loss of 2.4 ± 4.0 kg in the intervention group compared to 0.7 ± 3.3 kg in the control group. Adjusted analyses confirmed a significant between-group difference of −1.60 kg (95% CI −2.83 to −0.38; $p=0.011$). Ruize-Leon et al. [4] also conducted a 12-week RCT, there's resulted in a mean weight loss of 0.8 kg ($p=0.03$), BMI reduction of 0.3 kg/m² ($p=0.03$), and a 1.0 cm decrease in waist circumference ($p=0.046$) [10].

In contrast, Forman et al. (2019) evaluated a 10-week digital cognitive-behavioral therapy intervention (OnTrack) for weight loss with the weight watchers (WW) platform Beyond The Scale (BTS) vs. the weight watchers platform by itself as the control group. However, half way through the RCT the dynamics of the trial changed from using BTS to a Freestyle (FS) diet plan - a newly developed WW digital platform that was released during the study period. With these changes with design during the study, the results were unique in that only BTS-WW participants weight loss was greater for the intervention group (Mean change of = 4.7%, SE = 0.55) than for the control group (Mean change = 2.6%, SE = 0.80). Interestingly, the results were reversed for the FS-WW intervention participants (mean of 2.9%, SE = 0.38) vs. control group (mean change of 4.5%, SE = 0.52) [25]. Similarly, Persell et al. [23] conducted a 6-month RCT focused on changes in blood pressure, but measured secondary outcomes, one of which being change in BMI. They found a mean BMI change of–0.15 (95% CI −0.51 to 0.20; $p=0.39$) [23].

Among observational studies two single-arm fields trials by Khokhar et al. [1, 20] reviewing cardiometabolic effects of the same participant population base experienced a mean weight loss of *17.27 lbs.*, equating to a total body weight loss (BWL) of 13.9% with a mean BMI reduction of 8.6 points. Weekly weight loss averaged 0.71 kg [20]. Furthermore, 98.7% of participants achieved ≥ 5% weight loss, 75% achieving ≥ 10%, 43% achieved ≥ 15%, and 9% achieved ≥ 20% BWL [1, 20].

In a large cohort ($n>3000$), Graham et al. [9] found a mean weight nadir of 4.2% (4.4 kg) achieved at day 150, with 35% of the population achieving > 5% BWL. Among CDC-qualified program participants, mean weight loss increased to 7.0% (7.3 kg). Daily AI coach interaction was associated with a 0.8% increased likelihood of achieving 5% weight loss. Also, higher self-weighing frequency was independently associated with greater weight loss, supporting previously established literature on impact of self-weighing frequency on weight loss [9, 24]. Paz et al.

[14] conducted a retrospective analysis on engagement cardiometabolic changes after engagement with a digital lifestyle-medicine app tied with self-monitoring, with a weight cohort of 16,402 individuals. They classified reduction of weight in pounds by baseline BMI category and found that weight reduction was inversely related to BMI, with an average loss of 12.0 lbs (SEM 0.3) equating to a 5.1% weight loss among users with BMI $\geq$ 30 [14]. Colwell et al. [13] observed a combined BMI and weight loss improvement of 6.5% over 12 weeks in a large real-world cohort ($n=320$) based on lifestyle course lengths from 4 to 32 weeks, with statistically significant results ($p<0.01$) [13].

Additionally, 3 observational studies supported a modest weight loss: Lockwood et al. [21] completed a single-arm pilot study over 3 months ($n=509$) found an average weight loss of 3.8% (SD 2.9%; 95% CI 3.5%–4.1%) of baseline body weight. A total of 71.2% of participants achieved $\geq$ 2% weight loss, and 26.5% achieved $\geq$ 5% [16]. Stein et al. [2] evaluated a fully automated AI coach and found a mean weight loss of 2.4 kg (2.4% of body weight) over 15 weeks, with 75.7% of participants achieving weight loss during the intervention.[2] Maher et al. (2020) documented a mean weight loss of 1.1 kg by week 6 and a cumulative 1.3 kg by week 12 (95% CI −2.5 to −0.7; $p=0.01$). As well as a waist circumference decline of 2.1 cm over the 12-week period ($p=0.003$) [11].

Pediatric-Specific Results

Only 1 observational study reviewed pediatric populations: Zarkogianni et al. [3] evaluated the ENDORSE platform in a pediatric population and found a significant reduction in BMI z-score (mean -0.21 ± 0.26; $p<0.001$). A negative correlation was observed between use of an activity tracker and BMI z-score ($r=-0.355$; $p=0.017$) [3].

Taking both RCTs and observational study data together, these findings illustrate that AI-driven behavioral coaching intervention can achieve weight loss across diverse populations, settings, and delivery models. While the magnitude of change varied, ranging from modest (–0.8 kg) to highly clinically significant (–13.9% BWL). Many studies met or exceeded the 5% threshold considered beneficial for clinically significant weight loss. The most effective interventions often involved personalized feedback loops, predictive modeling, or integration with human coaching, suggesting that tailored engagement and hybrid designs may enhance outcomes.

Non-Weight Outcomes

Blood Pressure

Several studies reported outcomes related to blood pressure, highlighting the potential for AI-assisted behavioral interventions to positively influence cardiovascular risk factors. Shamanna et al. [5], completed an RCT that found the intervention group achieved significant reductions in systolic blood pressure (SBP) (−7.6 vs. −3.2 mm Hg; $p<0.007$) and diastolic blood pressure (DBP) (−4.3 vs. −2.2 mm Hg; $p=0.046$) after 1 year compared with the control group. They also found that among participants with HTN, the intervention group achieved higher rates of normotension (40.9% vs. 6.7%; $p=0.0009$) and HTN remission (50% vs. 0%; $p<0.0001$) than the control group [5].

Ruiz-Leon et al. [4], conducted a 12-week RCT evaluating a digital lifestyle intervention in older adults with overweight and obesity. The intervention group experienced −4.5mmHg (CI: −9.0 to 0.0) change in systolic BP compared to a −5.0mmHg (CI: −9.4 to −0.7) change in the control group with a difference of 1.3 (CI: −10.2−12.8), as well as a Diastolic BP, −2.4mmHg (CI:−4.4 to −0.3) in the intervention group vs. −0.4mmHg (CI: −2.5 to 1.6) in the control, a difference of −3.5 (CI: −8.9 to 1.8) over 12 weeks [4]. Thus all the data is not statistically significant.

Another RCT, Persell et al. [23] found that over the 6-month trial, the corresponding mean systolic blood pressures were 132.3mmHg (from a 140.6 mm Hg baseline) and 135.0 mm Hg (from a 141.8 mm Hg baseline), with a between-group adjusted difference of −2.0 mm Hg (95% CI, −4.9 mm Hg to 0.8 mm Hg; $p=0.16$). Interestingly they also found that at 6 months, self-confidence in controlling blood pressure was greater in the intervention group (0.36 point on a 5-point scale; 95% CI, 0.18 to 0.54 point; $p<0.001$) [23].

Branch et al. [16], completed a large observational study evaluation the effectiveness of an AI powered hypertension care app. Among 717 participants with baseline hypertension, the program resulted in a mean reduction of −5.4 mm Hg (95% CI −6.5 to −4.3; $p<0.01$) in SBP and −1.2 mm Hg (95% CI −2.1 to −0.5; $p<0.002$) in DBP over a 3-month engagement period. Notably, participants who experienced > 5% weight loss had significantly greater SBP and DBP reductions compared to those who did not lose weight, suggesting a synergistic effect on combined weight loss and digital engagement. The study also highlighted the level of engagement with the digital platform (e.g., app use frequency, logging behavior) was positively correlated with the magnitude of blood pressure improvement. To note, they also found that SBP and DBP changes were greatest in those with stage 2 hypertension [16].

Among the other observational study findings, Paz et al. [14] documented a substantial reduction in SBP of 18.6 mmHg after 24 weeks of AI-guided lifestyle modifications [14]. Similarly, Leitner et al. [15] led a trial utilizing an autonomous lifestyle-guidance system. They found an average SBP reduction of 8.1 mmHg over the 24-week course of the intervention [14]. In a large digital diabetes prevention program (DPP) analyzed by Graham et al. [9], mean SBP decreased by 5.4 mmHg at three months, and this reduction was sustained through six months.[9] These findings align with reductions commonly observed in traditional intensive lifestyle interventions and underscore the potential of AI tools to serve as scalable adjuncts to hypertension management.

Diastolic blood pressure (DBP) outcomes were specifically reported in three studies: Paz et al. [14], Graham et al. [9], and the autonomous lifestyle-guidance system trial. In the Paz et al. study, DBP declined by 9.4 mmHg; in the autonomous guidance system, DBP decreased by approximately 6.2 mmHg; and in the digital DPP analyzed by Graham et al., DBP was reduced by 3.2 mmHg [9, 14]. These consistent reductions in DBP reinforce the capacity of AI-driven tools to influence both components of blood pressure meaningfully. The degree of reduction was influenced by baseline hypertension severity, level of program adherence, and integration with other behavioral strategies like weight tracking and dietary logging.

Collectively, these findings suggest that AI-enabled coaching platforms may have beneficial effects on blood pressure regulation, particularly when integrated with weight loss strategies and real-time health monitoring. The magnitude of SBP reduction observed in some studies approaches the efficacy of first-line antihypertensive medications, supporting the role of digital coaching as a non-pharmacologic complement in managing hypertension in individuals at risk for obesity-related cardiometabolic disease.

Diabetes and Glycemic Control

Several studies reported on the effects of AI-assisted behavioral coaching on diabetes-related outcomes, particularly glycemic control. In the Greenhabit randomized controlled trial [4], a more modest yet clinically relevant HbA1c reduction of 0.4% points was observed, over a 1 week period [4]. Additionally, Joshi et al. [17] RCT, noted a significant decline in fasting glucose and HbA1c among individuals (−2.9 [1.8] vs. −0.3 [1.2]; $p<0.001$) at 1 year with 72.7% remission of T2D [4].

Colwell et al. [13], conducted an observational study on the Redicare digital twin–enabled platform showed one of the most significant improvements in glycemic metrics, with a reduction in hemoglobin A1c (HbA1c) of 1.2% points (10.9%, $n=80$, $p<0.01$) over the course of the intervention [13].

Lipids

Improvements in lipid parameters were also documented in one randomized control trials reviewed. Nakata et al. (2020) RCT over a 12-week timeframe calculated difference in HDL, LDL and triglycerides. They found that the HDL levels adjusted mean between groups at 12 weeks was 1.42 mg/dL (95% CI: −1.05, 3.89; $p=0.22$), LDL levels adjusted mean between groups at 12 weeks was −2.45 mg/dL (95% CI: −7.64, 2.74; $p=0.34$) and a triglyceride adjusted mean difference of −23.73 mg/dL (95% CI: −62.06, 14.6o; $p=0.22$) [10]. Although all p values indicate that the data was not significant it still provides a level of evidence for us to make assumptions and base future research on results.

A few observational studies also found some interesting data on lipid changes. Paz et al. [14] demonstrated a significant reduction in low-density lipoprotein cholesterol (LDL-C) of −66.6 mg/dL, accompanied by a 28% decline in triglyceride levels among users of a digitally guided behavior-change platform [14]. In a separate analysis, Colwell et al. [13] reported a 30% decrease in triglyceride levels after 12 weeks of participation in a hybrid AI-human coaching program [13].

Liver Function and Metabolic Health

Limited data were available regarding hepatic outcomes; Joshi et al. [17] completed an RCT and tracked participants in numerous hepatic markers of MASLD. Following intervention, they found a drastic increase in users towards normal MASLD-Liver Fat Scores (from 11.8 to 67.4% in the intervention group, whereas it reduced from 16 to 9.9% at 1 year in the standard care group ($p<0.00001$). Additionally, of the 10 patients in the intervention group with abnormal Fib-4 scores, 9 (90%) fell into the normal range at 1 year, compared to only 2 of the 8 (25%) in the standards of care group [17]. While preliminary, these findings warrant further investigation into the hepatometabolic impacts of AI-driven lifestyle modification.

Discussion

Our systematic review reveals that AI-enabled behavioral coaching can lead to clinically meaningful improvement in weight management, blood pressure, lipid levels, glycemic control, and lipid profiles. These benefits observed across a variety of study designs and populations, highlight the potential for AI to act as an effective adjunct or alternative to traditional lifestyle interventions. In several studies, outcomes approached or even exceeded the benchmarks commonly expected for pharmacological interventions.

Weight loss varied from modest to substantial, with the most impressive reductions observed in highly engaged participants using hybrid platforms that combined automated coaching with human oversight. These findings suggest that user-centered design and personalization may be critical to maximizing effectiveness. In addition to weight outcomes, improvements in HbA1c, lipid profiles, SBP, DBP and markers for MASLD were observed, supporting the cross-domain impact of these interventions.

However, the rapid integration of AI into health behavior change raises important ethical considerations. A lack of transparency around algorithm development, decision-making logic, and data governance emerged across the studies. None of the reviewed platforms disclosed detailed mechanisms for how health recommendations were generated, or discussed how the platform maintained HIPAA compliance or user data protection protocols. This lack of clarity, not only challenges reproducibility but also diminishes user trust and accountability [26–28].

It is imperative for us to establish ethical frameworks to guide the implementation of AI in healthcare. In 2021, the WHO released a set of six foundational principles for ethical AI in healthcare, emphasizing transparency, fairness, human oversight, and data privacy. Their guidance also called for robust data governance practices that prioritize informed patient consent and safeguard against misuse of personal health information [29]. Similarly, the AMA and AHA have put forth their own ethical considerations. These include regularly auditing AI systems to reduce the risk of perpetuating systemic bias and ensuring that AI tools are used to enhance, not replace, the patient-provider relationship. They also emphasize the importance of explainability and accountability in algorithmic decision-making [30, 31]. Despite the availability of these frameworks, none of the AIBC platforms reviewed in our study reported adherence to any of the aforementioned guidelines.

Digital equity represents another critical barrier. Most interventions required reliable access to smart phones, wearables, or continuous internet, a requirement that may exclude underserved communities and exacerbate existing health disparities. In addition, cultural adaptation and community involvement were rarely incorporated into program design. To ensure equitable impact, future platforms must prioritize inclusive design processes and consider the socioeconomic realities of diverse user populations.

Finally, the behavioral frameworks embedded in AI systems often draw from well-established psychological principles, such as goal setting, self-monitoring and motivational interviewing. When delivered consistently and responsively, these strategies enable scalable, high-frequency interventions not possible with traditional in-person one to one counseling. While more comparative research is needed, the hybrid AI-human model appears especially promising for maintaining clinical nuance without compromising efficiency.

Limitations of the Evidence Base

Despite these promising findings, several limitations should be acknowledged. Many studies were short in duration (often 3 months in duration), lacked control groups, or relied on self-reported data. A significant portion of the publications were industry-funded, raising concern for potential bias (industry sponsorship bias). Heterogeneity in intervention components, specifically the AIBC platform further complicates efforts to synthesize findings across studies.

Another important limitation is the rapid advancement of AI technology itself. Many of the studies included in this review were conducted several years ago, and as a result may not reflect the capabilities of current generation AI platforms. Improvements in natural language processing, machine learning algorithms, and personalization engines could render some older interventions obsolete or less relevant. This highlights the importance of continual reassessment and updated trials to keep pace with technological evolution.

Future Direction

To realize the full potential of AI in obesity management, future research must prioritize newer AI technologies, large-scale, independently funded RCTs with long-term follow-up. Comparative studies of AI-only, human-only, and hybrid models are needed to inform best practices. Moreover, consistent reporting standards for digital health interventions should be established, including transparent algorithm documentation and standardization by following clear ethical guidelines and oversight protocols to ensure safe, equitable and trustworthy use in clinical practice.

Implementation research will also be critical to bridge the gap between efficacy and real-world adoption. This includes developing equitable access models, culturally tailored content, and integration into primary care workflows.

Key References

- Joshi S, Paramesh Shamanna, Mala Dharmalingam, et al. Digital Twin Enabled Personalized Nutrition Improves Metabolic Dysfunction-Associated Fatty Liver Disease in Type 2 Diabetes: Results of a 1-Year Randomized Controlled Study. Endocrine Practice. Published online September 1, 2023. https://doi.org/10.1016/j.eprac.2023.08.016.

They conducted an open-label, multicentered RCT involving 319 particpants with type 2 diabetes, comparing a Digital Twin (DT), AIBC platform to standard care. The intervention group achieved statisitical significant improvements in weight loss (mean –7.4 kg), BMI (–2.7), waist circumference (–9.5 cm), and HbA1c (–2.9%), with 73.8% of participants losing more than 5% of their body weight and 72.7% achieving T2D remission. Additionally, substantial improvements were observed in hepatic markers related to metabolic dysfunction-associated fatty liver disease (MASLD), supporting the multifaceted impact of AI-driven interventions in metabolic care.

- Shamanna P, Joshi S, Dharmalingam M, et al. The impact of digital twin technology on HbA1c reduction and ASCVD risk in participants enrolled for type 2 diabetes remission: outcomes of RCCT at 1 year. Endocr Pract. 2024;30(Suppl 1):S73–S79.

  They evaluated the long-term effects of the same Digital Twin platform in a randomized controlled trial of 289 individuals with T2D and comorbid hypertension. At one year, the DT group achieved significant reductions in systolic (–7.6 mmHg) and diastolic blood pressure (–4.3 mmHg), with 50% attaining hypertension remission and 40.9% achieving normotension. Additional benefits included improvements in albuminuria and normoalbuminuria rates, suggesting the platform's utility in both metabolic and renal outcomes.

- Nakata Y, et al. AI-enhanced dietary coaching app improves nutrition tracking in Japanese adults. J Nutr Sci. 2023;12:e19.

  They performed a three-month randomized controlled trial (n = 141) evaluating the CALO Mama Plus smartphone app, which used AI to analyze diet, physical activity, and sleep data to provide real-time feedback. The intervention group achieved a statistically significant between-group difference in weight loss (–1.6 kg; p = 0.011). While changes in lipid levels did not reach statistical significance, the study demonstrated the short-term efficacy of AI-based coaching in a working adult population.

- Ruiz-Leon AM, Casas R, Castro-Barquero S, et al. Efficacy of a mobile health–based behavioral treatment for lifestyle modification in type 2 diabetes self-management: Greenhabit randomized controlled trial. J Med Internet Res. 2025;27:e58319.

  They conducted a 12-week, single-blind randomized controlled trial involving 123 adults recently diagnosed with T2D. The intervention group used the Greenhabit AI-based app, which offered personalized lifestyle coaching through a recommender system. Results showed meaningful reductions in body weight (–0.8 kg), BMI (–0.3), waist circumference (–1.0 cm), HbA1c (–0.4%), SBP (–4.5 mmHg), and DBP (–2.4 mmHg). Improvements were also noted in HDL and triglyceride levels, underscoring the intervention's multidimensional benefits.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12170-025-00776-7.

Author Contributions RH, NM & NP wrote the main manuscript text. RH, NP & JR reviewed and edited the main manuscript. RH, NM & NG completed the SR chart. RH, NM & NG completed the preliminary and secondary review of all the publications collected in our search. MP & CK conducted the collection of publications for review and organized publications into the Covidence platform prior to review.

Funding No funding was received.

Data Availability No datasets were generated or analysed during the current study.

Declarations

Competing Interests The authors declare no competing interests.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

References

1. Khokhar S, Choudhary R, Khandelwal D, et al. Real-world implementation of an AI-powered diabetes coaching app: preliminary findings from South Asia. Endocr Pract. 2024;30(Suppl 1):S73.
2. Stein N, Brooks K. A fully automated conversational artificial intelligence for weight loss: longitudinal observational study among overweight and obese adults. JMIR Diabetes. 2017;2(2):e28.

3. Zarkogianni K, Chatzidaki E, Polychronaki N, et al. The ENDORSE feasibility study: exploring the use of m-health, artificial intelligence and serious games for managing childhood obesity. Nutrients. 2023;15(6):1451.
4. Ruiz-Leon AM, Casas R, Castro-Barquero S, et al. Efficacy of a mobile health–based behavioral treatment for lifestyle modification in type 2 diabetes self-management: greenhabit randomized controlled trial. J Med Internet Res. 2025;27:e58319.
5. Shamanna P, Joshi S, Dharmalingam M, et al. The impact of digital twin technology on HbA1c reduction and ASCVD risk in participants enrolled for type 2 diabetes remission: outcomes of RCCT at 1 year. Endocr Pract. 2024;30(Suppl 1):S73–9.
6. Patra E, Kokkinopoulou A, Wilson-Barnes S, et al. Personal goals, user engagement, and meal adherence within a personalised AI-based mobile application for nutrition and physical activity. Life. 2024;14:1238.
7. Shamanna P, et al. Digital twin in managing hypertension among people with type 2 diabetes: 1-year randomized trial. JACC Adv. 2024;3:101172.
8. Fadhil A, Wang Y, Reiterer H. Assistive conversational agent for health coaching: validation and usability study. JMIR Form Res. 2019;3(1):e10944.
9. Graham SA, Pitter V, Hori JH, et al. Weight loss in a digital app-based diabetes prevention program powered by artificial intelligence. Digit Health. 2022;8: 1–12.
10. Nakata Y, et al. AI-enhanced dietary coaching app improves nutrition tracking in Japanese adults. J Nutr Sci. 2023;12:e19.
11. Maher JP, et al. Paola: a virtual coach for healthy aging. Transl Behav Med. 2024;14(1):tbac098.
12. Patra E, et al. Personal goals and adherence in AI-driven mobile nutrition support: results from PROTEIN study. Life. 2024;14:1238.
13. Colwell N, et al. 61 Artificial intelligence mediated real-time lifestyle intervention significantly reduces multiple cardiovascular risk factors in patients. Heart (British Cardiac Society). 2023;109(Suppl 6):A69–70. https://doi.org/10.1136/heartjnl-2023-ICS.61.
14. Paz E, Michos ED, Zimlichman E, et al. Comprehensive cardiovascular risk factor control with a mobile health cardiovascular risk self-management program. J Am Heart Assoc. 2024;13(10):e033328. https://doi.org/10.1161/JAHA.123.033328.
15. Leitner J, Chiang PH, Agnihotri P, Dey S. The effect of an AI-based, autonomous, digital health intervention using precise lifestyle guidance on blood pressure in adults with hypertension: single-arm nonrandomized trial. JMIR Cardio. 2024;8:e51916. https://doi.org/10.2196/51916.
16. Branch OH, Rikhy M, Auster-Gussman LA, Lockwood KG, Graham SA. Relationships between blood pressure reduction, weight loss, and engagement in a digital app–based hypertension care program: observational study. JMIR formative Res. 2022;6(10): e38215. https://doi.org/10.2196/38215.
17. Joshi S, Paramesh S, Dharmalingam M, et al. Digital twin enabled personalized nutrition improves metabolic dysfunction-associated fatty liver disease in type 2 diabetes: results of a 1-Year randomized controlled study. Endocrine practice. Published online September 1. 2023. https://doi.org/10.1016/j.eprac.2023.08.016.
18. Chew HSJ, Chew NW, Loong SSE, et al. Effectiveness of an artificial intelligence-assisted app for improving eating behaviors: mixed methods evaluation. J Med Internet Res. 2024;26:e62767. https://doi.org/10.2196/62767.
19. Ellen E, Fitzsimmons-Craft GN, Rackoff, Shah J et al. Effects of chatbot components to facilitate mental health services use in individuals with eating disorders following online screening: an optimization randomized controlled trial. Int J Eat Disorders Published Online July 28. 2024. https://doi.org/10.1002/eat.24260
20. Khokhar S, Holden J, Toomer CH. Whitby4 L. Efficacy of an AI-based weight loss digital therapeutics platform: A multidisciplinary perspective. AIHealth 2024: The First International Conference on AI-Health. Published online. 2024. https://personales.upv.es/thinkmind/dl/conferences/aihealth/aihealth_2024/aihealth_2024_1_110_80055.pdf. Accessed 29 May 2025.
21. Lockwood KG, Kulkarni PR, Paruthi J, et al. Evaluating a new digital app–based program for heart health: feasibility and acceptability pilot study. JMIR Form Res. 2024;8: e50446–50446.
22. McNulty C, Holland J, McDonald C, McGee MJ. The impact of an AI-driven personal health platform on cardiovascular disease risk. Smart Health. 2024;33:100499. https://doi.org/10.1016/j.smhl.2024.100499.
23. Persell SD, Peprah YA, Lipiszko D, et al. Effect of home blood pressure monitoring via a smartphone hypertension coaching application or tracking application on adults with uncontrolled hypertension: A randomized clinical trial. JAMA Netw Open. 2020;3(3):e200255–200255. https://doi.org/10.1001/jamanetworkopen.2020.0255.
24. Hallock R, Ufholz K, Patel N. Self-Monitoring of weight as a weight loss strategy: A systematic review. Curr Cardiovasc Risk Rep. 2024;18:163–72. https://doi.org/10.1007/s12170-024-00746-5.
25. Forman EM, Goldstein SP, Crochiere RJ, Butryn ML, Juarascio AS, Zhang F, Foster GD. Randomized controlled trial of OnTrack, a just-in-time adaptive intervention designed to enhance weight loss. Transl Behav Med. 2019;9(6):989–1001. https://doi.org/10.1093/tbm/ibz137.
26. Beam AL, Manrai AK, Ghassemi M. Challenges to the reproducibility of machine learning models in health care. JAMA. 2020;323(4):305–6. https://doi.org/10.1001/jama.2019.20866.
27. Sohn Emily. The reproducibility issues that haunt health-care AI. Nat. 2023;613(7943):402–3. https://doi.org/10.1038/d41586-023-00023-2.
28. Maguluri KK, et al. Advancing patient privacy in the era of artificial intelligence: A deep learning approach to ensuring compliance with HIPAA and addressing ethical challenges in Healthcare Data Security. 2024. https://doi.org/10.47059/IJMTLM/V27I5/030
29. WHO. Ethics and governance of artificial intelligence for health. Www who Int Published June 28. 2021. https://www.who.int/publications/i/item/9789240029200. Accessed 21 June 2025.
30. Augmented intelligence in medicine. American Medical Association. Published. April 2025. https://www.ama-assn.org/practice-management/digital-health/augmented-intelligence-medicine. Accessed 21 June 2025.
31. Armoundas AA, Narayan SM, Arnett DK, et al. Use of artificial intelligence in improving outcomes in heart disease: A scientific statement from the American heart association. Circulation. 2024;149(14). https://doi.org/10.1161/cir.0000000000001201. Accessed 21 June 2025.