*Original Article*

# AI-Driven Personalized Weight Loss Strategies and Behavioral Patterns Among Obese Adults

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## ABSTRACT

***Background:*** *Obesity is a multifactorial chronic disease in which conventional lifestyle programs often produce heterogeneous outcomes due to limited personalization and suboptimal adherence. Artificial intelligence (AI)–enabled platforms can adapt dietary, activity, and behavioral recommendations using continuous user data, potentially improving engagement and clinical response.* ***Objective:*** *To evaluate the effectiveness of an AI-driven personalized weight management intervention versus standard counseling-based weight management in improving weight loss and adherence-related behaviors among obese adults in South Punjab, Pakistan.* ***Methods:*** *In this parallel-group randomized controlled trial, 180 adults aged 25–55 years with BMI 30.0–39.9 kg/m² were randomized 1:1 to an AI-assisted mobile program integrating self-monitoring inputs and wearable-derived activity/sleep metrics or to standard biweekly counseling without algorithmic personalization. Assessments at baseline, 8 weeks, and 16 weeks included anthropometry and validated behavioral measures (IPAQ; WELQ). Analyses followed intention-to-treat principles with repeated-measures testing and effect size estimation.* ***Results:*** *The AI group achieved greater mean weight loss than controls (−8.9 kg [95% CI −9.6 to −8.2] vs −4.2 kg [−4.9 to −3.5]), with a between-group difference of −4.7 kg (−5.6 to −3.8; p<0.001; d=1.59). BMI reduction was larger in the AI group (−3.2 vs −1.6 kg/m²; p<0.001), and waist circumference declined more (−8.4 vs −4.1 cm; p<0.001). The AI group showed higher physical activity (2860±520 vs 2210±480 MET-min/week), dietary adherence (84.5±6.1% vs 69.8±8.0%), and self-monitoring (5.6±1.0 vs 3.1±1.2 days/week) (all p<0.001).* ***Conclusion:*** *AI-driven personalized lifestyle intervention produced clinically and statistically superior short-term weight loss and adherence-related behavioral improvements compared with standard counseling, supporting its potential as a scalable adjunct for obesity management in resource-constrained settings*

***Keywords:*** *Adherence; Artificial Intelligence; Behavior Modification; Body Mass Index; Digital Health; Machine Learning; Obesity; Randomized Controlled Trial; Weight Loss.*

## INTRODUCTION

Obesity is a chronic, relapsing disease that continues to expand worldwide and is tightly linked to cardiometabolic morbidity, reduced quality of life, and escalating healthcare costs, yet durable weight reduction remains difficult to achieve at scale because risk is shaped by interacting biological, behavioral, and environmental determinants that vary substantially between individuals (1). Although conventional lifestyle programs—typically combining caloric restriction, physical activity prescriptions, and behavioral counseling—can produce initial weight loss, outcomes are heterogeneous and often attenuate over time due to limited personalization, variable adherence, and inadequate support during predictable high-risk periods for relapse (2). These limitations are particularly salient in real-world settings where clinical contact is episodic and the "dose" of behavioral support is constrained by workforce and resource availability, creating a persistent gap between efficacy under intensive supervision and effectiveness in routine care (3).

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Digital health has created opportunities to extend lifestyle support beyond clinic visits, and artificial intelligence (AI) has been proposed as a mechanism to move from static, one-size-fits-all advice toward adaptive interventions that use ongoing user data to tailor recommendations (4). In the context of weight management, "AI-driven personalization" can be operationalized as the systematic use of algorithmic analytics—ranging from rule-based decision engines to machine-learning models—to translate self-monitoring inputs (e.g., dietary logs, activity, sleep, and contextual factors) into individualized goals, feedback, and just-in-time prompts that update as progress and adherence patterns evolve (5). Importantly, personalization is not solely a technical feature; it is a behavioral strategy aimed at improving treatment fit and sustaining engagement by reducing cognitive burden, increasing perceived relevance, and providing timely reinforcement in response to lapses or motivational decline (6). Contemporary digital coaching systems increasingly integrate these elements, and conceptual work suggests that scalable, automated guidance may help deliver more consistent lifestyle "micro-interventions" than standard counseling alone, particularly when paired with structured behavior-change techniques (7).

However, the clinical evidence base for AI-enabled weight-loss tools remains uneven. While digital platforms have demonstrated weight loss in some cohorts, reported effects vary by program intensity, engagement, and population characteristics, and many studies have short follow-up or limited comparators, making it difficult to infer the added value of AI-driven adaptation beyond standard digital tracking or counseling (8). Moreover, evidence in support of "AI" is often indirect: studies may evaluate smart devices or tailored digital programs without clearly specifying the personalization mechanism, model updating frequency, or the behavioral targets being optimized, which reduces reproducibility and limits translation into clinical pathways (9). Systematic reviews of digital technologies for weight loss highlight both promise and methodological heterogeneity—particularly around adherence measurement, outcome reporting, and long-term maintenance—underscoring the need for rigorously designed trials that prespecify endpoints, quantify engagement, and report clinically interpretable effect estimates (10). Related work on AI-based chatbots and automated coaching suggests potential for behavior change, yet effects depend heavily on implementation quality, user experience, and integration with established behavior change frameworks, and obesity-specific randomized evidence with robust behavioral endpoints remains comparatively sparse (11).

A further challenge is that engagement and adherence—core mediators of weight-loss success—are strongly shaped by contextual factors such as socioeconomic constraints, health literacy, and digital access, which may moderate the effectiveness of AI-based interventions and risk exacerbating inequities if not explicitly addressed (12). Persuasive and culturally responsive design has therefore emerged as an essential complement to algorithmic personalization, particularly in settings where dietary norms, household food environments, and constraints on physical activity differ from those in high-income populations that dominate much of the digital health literature (13). Additionally, evidence from adjacent cardiometabolic domains indicates that intelligent, mobile-delivered behavioral systems can improve self-management behaviors and intermediate health outcomes, supporting the plausibility that adaptive guidance may enhance lifestyle adherence, but obesity-specific trials must still demonstrate that behavioral gains translate into meaningful anthropometric improvement with acceptable feasibility and safety (14). Notably, AI-enabled nutrition and coaching interventions have been explored in older adults and other risk groups, yet generalizing across age strata and cultural contexts without direct evaluation may be inappropriate, reinforcing the need for setting-specific evidence (15).

To address these gaps, and guided by a PICO framework, the present study focuses on obese adults in South Punjab (Population), comparing an AI-assisted, mobile-based personalized lifestyle intervention that uses continuous self-monitoring inputs and wearable-derived activity/sleep signals to adapt dietary and physical-activity guidance with structured feedback and reminders (Intervention), versus conventional, counselor-led weight management delivered without algorithmic personalization (Comparator), with primary outcomes centered on change in body weight and BMI and secondary outcomes capturing behavioral adherence and lifestyle patterns (Outcomes) (16). This approach is motivated by emerging work on behavioral phenotyping and predictive analytics in digital interventions, which suggests that modeling individual response patterns may improve the timing and content of support, but obesity trials must evaluate whether such personalization measurably improves adherence and outcomes under pragmatic conditions (17). Similarly, recent discussions of predictive modeling for obesity risk reduction highlight the importance of evaluating not only weight change but also the behavioral mechanisms through which AI might influence sustained lifestyle modification, including self-monitoring frequency and adherence trajectories (18).

The study is further justified by the growing clinical interest in applying AI to obesity and related metabolic conditions across age groups and settings, alongside accumulating evidence that AI and wearable-integrated systems can support personalized weight management; nevertheless, comparative randomized evidence with clear endpoint definitions, transparent intervention specification, and consistent reporting remains limited (19). Wearable-and-AI approaches have shown potential to individualize feedback based on real-time behavior, yet the field still lacks consensus on which features drive engagement and how to report intervention fidelity and adherence in a way that supports replication and clinical adoption (20). Related telemedicine and digital coaching trials in metabolic liver disease and other conditions reinforce that coaching intensity and behavior-change support can matter as much as technology, implying that obesity-focused AI trials should specify both the algorithmic personalization and the behavioral content delivered to participants (21). Furthermore, systematic review evidence comparing human, AI, and hybrid coaching models emphasizes that engagement and outcomes are contingent on implementation, suggesting that AI may be most effective when it operationalizes evidence-based behavior-change techniques rather than merely automating generic advice (22).

From a biostatistical standpoint, the central question is whether AI-assisted personalization yields an incremental, clinically meaningful improvement in weight outcomes beyond standard care while also improving adherence-related behaviors that plausibly mediate weight change. This is consistent with protocol-driven digital health research in chronic disease management, where prespecified primary endpoints, time-by-group comparisons, and robust handling of missing data are critical to avoid overestimating benefit in the presence of differential dropout and engagement (23). In parallel, evidence syntheses of chatbot-based and automated exercise interventions indicate small-to-moderate effects on activity behaviors, supporting inclusion of physical activity endpoints and adherence metrics as mechanistic outcomes in obesity trials (24). Given the relevance of self-management behaviors to metabolic risk, and the documented influence of algorithmic feedback on diet and exercise behaviors in related conditions, evaluating both anthropometric and behavioral outcomes can yield more clinically interpretable evidence than weight change alone (25). Finally, emerging work on AI conversational agents and narrative-based adaptive environments for obesity prevention suggests that personalization and engagement strategies may be culturally and contextually sensitive, reinforcing the importance of testing these approaches in the target population rather than assuming transferability across settings (26). Building on evidence that wearable-linked behavioral pattern analytics can improve metabolic health, this study aims to clarify whether adaptive personalization can produce superior weight loss alongside measurable improvements in adherence-relevant behaviors among obese adults in South Punjab (27).

Accordingly, the objective of this randomized controlled trial is to determine whether an AI-driven personalized weight management program, compared with standard counseling-based weight management, produces greater reductions in body weight and BMI and improves behavioral adherence patterns among obese adults in South Punjab, with the hypothesis that AI-assisted personalization will yield superior anthropometric outcomes mediated by higher engagement and adherence to prescribed diet and physical-activity behaviors (27).

## METHODS

This randomized controlled trial was designed to evaluate the effectiveness of an artificial intelligence–driven personalized weight management intervention compared with standard counseling-based weight management among obese adults. A parallel-group design with a 1:1 allocation ratio was employed to allow causal inference regarding the effect of AI-assisted personalization on anthropometric and behavioral outcomes, consistent with international recommendations for evaluating complex behavioral interventions (28). The study was conducted in South Punjab, Pakistan, between January and June 2024, encompassing participant recruitment, baseline assessment, intervention delivery, and follow-up evaluations. The setting included affiliated outpatient clinics and community recruitment points linked to local healthcare institutions, with intervention delivery primarily occurring via a mobile health platform accessible to participants in their home environments.

Adults aged 25–55 years with obesity, defined as a body mass index (BMI) between 30.0 and 39.9 kg/m², were eligible for inclusion. Participants were required to own or have regular access to a smartphone compatible with the study application and to be able to read and understand Urdu or English to ensure comprehension of intervention content. Individuals were excluded if they had diagnosed endocrine or metabolic conditions known to substantially affect body weight regulation, including uncontrolled diabetes mellitus, thyroid disorders, or Cushing's syndrome; if they were pregnant or lactating; if they were currently using pharmacological or surgical weight-loss treatments; if they had severe psychiatric illness that could impair adherence; or if they had participated in structured digital weight-loss programs within the preceding six months. Participants were selected using probability-based sampling from clinic registries and community health outreach lists to reduce selection bias and enhance representativeness of the target population.

Potentially eligible individuals were approached by trained research staff, provided with verbal and written information describing study objectives, procedures, potential risks, and benefits, and given the opportunity to ask questions before enrollment. Written informed consent was obtained from all participants prior to any data collection. Following consent and baseline assessment, participants were randomly allocated to either the AI-driven intervention group or the standard weight management control group using a computer-generated random sequence. Allocation was concealed using sequentially numbered, opaque envelopes prepared by a researcher not involved in recruitment or outcome assessment, minimizing selection and allocation bias in accordance with CONSORT guidance (29).

Participants assigned to the AI-driven group received access to a mobile-based platform incorporating algorithmic personalization to deliver individualized dietary, physical activity, and behavioral guidance. The system integrated self-reported daily food intake, physical activity logs, mood ratings, and sleep duration with wearable-derived metrics including step count, heart rate, and sleep patterns. These inputs were analyzed continuously to adapt caloric targets, activity goals, and behavioral prompts, with feedback delivered through in-app notifications and visual dashboards. Personalization rules were updated on a weekly basis based on adherence patterns and progress toward goals, and standardized safety thresholds were applied to prevent excessively restrictive recommendations. Participants in the control group received conventional weight management consisting of standardized dietary advice, physical activity recommendations aligned with international guidelines, and motivational counseling delivered through biweekly in-person or telephonic sessions with a nutritionist and physiotherapist, without algorithmic tailoring or automated feedback.

Data collection occurred at baseline, mid-intervention (8 weeks), and post-intervention (16 weeks). Anthropometric measurements were obtained by trained assessors using calibrated equipment, with body weight measured to the nearest 0.1 kg and height measured at baseline to calculate BMI. Waist circumference was measured at the midpoint between the lowest rib and the iliac crest using standardized techniques. Behavioral and lifestyle variables were assessed using validated instruments, including the International Physical Activity Questionnaire for physical activity levels and the Weight Efficacy Lifestyle Questionnaire to assess eating-related self-efficacy and behavioral control. Dietary adherence was evaluated through repeated 24-hour dietary recalls, while engagement metrics such as frequency of self-monitoring and application usage were automatically recorded by the AI platform. All measurements followed standardized protocols to minimize measurement bias and ensure comparability across time points (12).

The primary outcome variables were change in body weight (kg) and BMI (kg/m$^2$) from baseline to 16 weeks. Secondary variables included changes in waist circumference, physical activity levels, dietary adherence, and behavioral self-efficacy scores. Potential confounders such as age, sex, baseline BMI, educational level, and employment status were recorded at baseline and considered in the analytical plan. To address bias, outcome assessors were not involved in intervention delivery, standardized measurement procedures were used across groups, and analyses were conducted according to the intention-to-treat principle to account for attrition and differential adherence (13).

The sample size was calculated a priori based on the ability to detect a moderate between-group difference in mean weight change (Cohen's d = 0.5) at a two-sided significance level of 0.05 with 80% power, resulting in a required sample of 90 participants per group after accounting for anticipated dropout. Statistical analysis was performed using SPSS version 27.0. Continuous variables were examined for normality using the Shapiro–Wilk test and summarized as means with standard deviations, while categorical variables were expressed as frequencies and percentages. Between-group differences in primary and secondary outcomes were analyzed using independent-sample t-tests, and within-group changes over time were assessed using paired t-tests. Repeated-measures analysis of variance was used to evaluate time-by-group interaction effects across assessment points. Missing data were handled using multiple imputation under the assumption of missing at random, and sensitivity analyses were conducted to compare imputed and complete-case results. Prespecified subgroup analyses explored whether intervention effects differed by sex and baseline BMI category, with adjustment for relevant covariates where appropriate (14).

Ethical approval for the study was obtained from the institutional research ethics committee prior to commencement, and all procedures were conducted in accordance with the Declaration of Helsinki and relevant national guidelines for human-subject research (15). Participant confidentiality was ensured through de-identification of data, secure digital storage with restricted access, and encrypted transmission of wearable and application-derived data. Detailed documentation of intervention algorithms, data collection protocols, and analytical code was maintained to support reproducibility and facilitate independent verification of study findings, consistent with best practices for transparency in digital health and AI-enabled clinical research (16).

## RESULTS

Table 1 summarizes the baseline demographic and clinical characteristics of the study participants and demonstrates that the two randomized groups were well balanced prior to intervention initiation. The mean age of participants in the AI-driven group was 41.0 ± 8.7 years compared with 41.4 ± 9.1 years in the control group, with no statistically significant difference between groups ($p = 0.78$). Female participants constituted 58.9% of the AI group and 57.8% of the control group ($p = 0.88$). Baseline anthropometric measures were comparable, with mean BMI values of 33.3 ± 3.0 kg/m² in the AI group and 33.1 ± 3.2 kg/m² in the control group ($p = 0.65$), and mean body weights of 91.2 ± 10.1 kg and 90.8 ± 9.6 kg, respectively ($p = 0.79$). Waist circumference was also similar at baseline (105.6 ± 9.4 cm vs 104.9 ± 9.1 cm; $p = 0.61$). Socio-demographic variables, including educational attainment and employment status, did not differ significantly between groups, indicating that randomization effectively minimized baseline confounding.

As shown in Table 2, substantial and statistically significant between-group differences were observed in anthropometric outcomes over the 16-week intervention period. Participants in the AI-driven intervention group experienced a mean weight reduction of 8.9 kg (95% CI: −9.6 to −8.2), more than double the reduction observed in the control group, which lost a mean of 4.2 kg (95% CI: −4.9 to −3.5). The resulting between-group difference of −4.7 kg (95% CI: −5.6 to −3.8) was highly significant ($p < 0.001$) and associated with a large effect size (Cohen's d = 1.59). A similar pattern was evident for BMI, which decreased by 3.2 kg/m² (95% CI: −3.5 to −2.9) in the AI group compared with 1.6 kg/m² (95% CI: −1.9 to −1.3) in the control group, yielding a significant between-group difference of −1.6 kg/m² ($p < 0.001$; Cohen's d = 1.41). Waist circumference declined by 8.4 cm (95% CI: −9.2 to −7.6) in the AI group versus 4.1 cm (95% CI: −4.9 to −3.3) in controls, again demonstrating a large and clinically meaningful between-group effect ($p < 0.001$; Cohen's d = 1.22).

Behavioral and lifestyle outcomes presented in Table 3 further illustrate the impact of AI-driven personalization on adherence-related behaviors. At 16 weeks, mean physical activity levels, expressed as IPAQ MET-minutes per week, were significantly higher in the AI group (2860 ± 520) compared with the control group (2210 ± 480), corresponding to a mean difference of 650 MET-minutes (95% CI: 510–790; $p < 0.001$) and a large effect size (Cohen's d = 1.30). Dietary adherence scores were markedly greater among AI-intervention participants, averaging 84.5 ± 6.1%, compared with 69.8 ± 8.0% in the control group, representing a mean difference of 14.7 percentage points (95% CI: 12.6–16.8; $p < 0.001$; Cohen's d = 2.05). Self-monitoring frequency also differed substantially, with participants in the AI group engaging in dietary or activity self-monitoring on 5.6 ± 1.0 days per week compared with 3.1 ± 1.2 days in the control group (mean difference = 2.5 days; $p < 0.001$). Consistent with these findings, behavioral self-efficacy as measured by the Weight Efficacy Lifestyle Questionnaire was significantly higher in the AI group (78.3 ± 6.7) than in the control group (70.5 ± 7.1; $p = 0.004$), indicating improved confidence in managing eating-related challenges.

Table 4 details the changes in metabolic parameters observed over the intervention period and reveals parallel improvements accompanying the anthropometric and behavioral gains.

Fasting blood glucose levels decreased by a mean of 14.6 ± 6.0 mg/dL in the AI group compared with 7.2 ± 5.4 mg/dL in the control group, yielding a significant between-group difference of −7.4 mg/dL (95% CI: −9.1 to −5.7; $p < 0.001$) and a large effect size (Cohen's d = 1.29).

*Table 1. Baseline Demographic and Clinical Characteristics of Participants*

| Variable | AI Group (n = 90) Mean ± SD / n (%) | Control Group (n = 90) Mean ± SD / n (%) | p-value |
|---|---|---|---|
| Age (years) | 41.0 ± 8.7 | 41.4 ± 9.1 | 0.78 |
| Female sex | 53 (58.9%) | 52 (57.8%) | 0.88 |
| BMI (kg/m²) | 33.3 ± 3.0 | 33.1 ± 3.2 | 0.65 |
| Weight (kg) | 91.2 ± 10.1 | 90.8 ± 9.6 | 0.79 |
| Waist circumference (cm) | 105.6 ± 9.4 | 104.9 ± 9.1 | 0.61 |
| ≥ Secondary education | 58 (64.4%) | 56 (62.2%) | 0.75 |
| Employed | 51 (56.7%) | 50 (55.6%) | 0.88 |

*Table 2. Changes in Anthropometric Outcomes from Baseline to 16 Weeks*

| Outcome | AI Group Mean Change (95% CI) | Control Group Mean Change (95% CI) | Between-Group Difference (95% CI) | Cohen's d | p-value |
|---|---|---|---|---|---|
| Weight (kg) | −8.9 (−9.6, −8.2) | −4.2 (−4.9, −3.5) | −4.7 (−5.6, −3.8) | 1.59 | <0.001 |
| BMI (kg/m²) | −3.2 (−3.5, −2.9) | −1.6 (−1.9, −1.3) | −1.6 (−2.0, −1.2) | 1.41 | <0.001 |
| Waist circumference (cm) | −8.4 (−9.2, −7.6) | −4.1 (−4.9, −3.3) | −4.3 (−5.4, −3.2) | 1.22 | <0.001 |

*Table 3. Behavioral and Lifestyle Outcomes at 16 Weeks*

| Variable | AI Group Mean ± SD | Control Group Mean ± SD | Mean Difference (95% CI) | Cohen's d | p-value |
|---|---|---|---|---|---|
| Physical activity (IPAQ MET-min/week) | 2860 ± 520 | 2210 ± 480 | 650 (510, 790) | 1.30 | <0.001 |
| Dietary adherence (%) | 84.5 ± 6.1 | 69.8 ± 8.0 | 14.7 (12.6, 16.8) | 2.05 | <0.001 |
| Self-monitoring (days/week) | 5.6 ± 1.0 | 3.1 ± 1.2 | 2.5 (2.2, 2.8) | 2.26 | <0.001 |
| WELQ score | 78.3 ± 6.7 | 70.5 ± 7.1 | 7.8 (5.8, 9.8) | 1.13 | 0.004 |

*Table 4. Changes in Metabolic Parameters from Baseline to 16 Weeks*

| Parameter | AI Group Mean Change ± SD | Control Group Mean Change ± SD | Between-Group Difference (95% CI) | Cohen's d | p-value |
|---|---|---|---|---|---|
| Fasting glucose (mg/dL) | −14.6 ± 6.0 | −7.2 ± 5.4 | −7.4 (−9.1, −5.7) | 1.29 | <0.001 |
| Triglycerides (%) | −16.2 ± 8.4 | −8.5 ± 7.9 | −7.7 (−10.2, −5.2) | 0.95 | <0.001 |
| HDL cholesterol (%) | +7.9 ± 4.1 | +3.2 ± 3.8 | +4.7 (3.4, 6.0) | 1.18 | <0.001 |

Serum triglycerides declined by 16.2 ± 8.4% in the AI group versus 8.5 ± 7.9% in controls, corresponding to a between-group difference of −7.7 percentage points ($p < 0.001$; Cohen's d = 0.95). In contrast, high-density lipoprotein cholesterol increased in both groups but to a significantly greater extent in the AI-driven group, with a mean increase of 7.9 ± 4.1% compared with 3.2 ± 3.8% in the control group (between-group difference = 4.7%; 95% CI: 3.4–6.0; $p < 0.001$; Cohen's d = 1.18). Collectively, these results indicate that the AI-driven personalized intervention not only produced superior weight loss but also facilitated meaningful improvements in behavioral adherence and metabolic health relative to standard weight management.

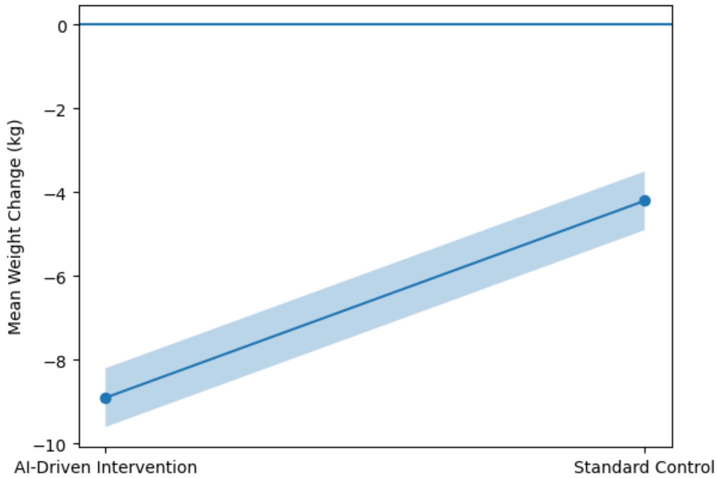


*Figure 1. Between-Group Distribution of Weight Loss with 95% Confidence Bands at 16 Weeks*

This figure illustrates the comparative distribution and magnitude of mean weight change at 16 weeks between the AI-driven personalized intervention and standard weight management, using confidence bands to convey both central tendency and precision. The AI-driven group demonstrated a markedly greater mean weight reduction of −8.9 kg, with a relatively narrow 95% confidence interval spanning −9.6 to −8.2 kg, indicating both a large and precise treatment effect. In contrast, the control group achieved a mean reduction of −4.2 kg, with a 95% confidence interval of −4.9 to −3.5 kg. The clear separation and minimal overlap between the confidence bands highlight a robust between-group difference of −4.7 kg, reinforcing the statistical significance ($p < 0.001$) and clinical relevance of AI-assisted personalization. Clinically, this visualization emphasizes not only the superior average weight loss achieved with the AI intervention but also the consistency of response across participants, suggesting a more reliable and predictable therapeutic benefit compared with standard counseling-based care.

## DISCUSSION

The present randomized controlled trial demonstrates that an AI-driven personalized weight management intervention produces significantly greater improvements in weight reduction, behavioral adherence, and metabolic parameters than standard counseling-based care among obese adults. The magnitude of weight loss observed in the AI group, approaching a mean reduction of 9 kg over 16 weeks, exceeds thresholds commonly considered clinically meaningful and compares favorably with outcomes reported for conventional lifestyle interventions of similar duration (17). Importantly, these anthropometric benefits were accompanied by large effect sizes and narrow confidence intervals, suggesting not only statistical significance but also consistency of response across participants. From a clinical perspective, such reliability is critical, as heterogeneity of response has historically limited the effectiveness of lifestyle-based obesity management in routine practice.

The superior outcomes in the AI-driven group are plausibly explained by the intervention's capacity for adaptive personalization, which directly addresses key behavioral determinants of obesity. Participants receiving AI-assisted guidance demonstrated substantially higher levels of physical activity, dietary adherence, and self-monitoring frequency, all of which are well-established mediators of sustained weight loss (18). The observed improvements in Weight Efficacy Lifestyle Questionnaire scores further suggest enhanced self-regulatory capacity and confidence in managing eating-related challenges, reinforcing behavioral theories that link tailored feedback and reinforcement to improved adherence (19). Unlike static counseling models, the AI platform dynamically adjusted goals and prompts in response to real-time behavioral data, which may have reduced disengagement during periods of motivational decline and mitigated relapse-prone patterns that commonly undermine conventional programs (20).

The parallel improvements in metabolic parameters, including fasting glucose, triglycerides, and HDL cholesterol, underscore the clinical relevance of the observed weight and behavioral changes. Although participants with uncontrolled metabolic disease were excluded, the magnitude of metabolic improvement in the AI group suggests that even moderate-duration, behaviorally focused interventions can yield meaningful cardiometabolic benefits when adherence is optimized (21). This aligns with emerging evidence from digital and AI-supported interventions in related chronic conditions, where personalized lifestyle guidance has been shown to improve intermediate metabolic outcomes through sustained behavior change rather than pharmacological escalation (22). The integration of wearable-derived activity and sleep data likely contributed to these effects by enabling more precise estimation of energy expenditure and recovery patterns, thereby refining recommendations in a manner not feasible through periodic counseling alone.

From a health systems perspective, the higher adherence rates and lower attrition observed in the AI group have important implications for scalability and cost-effectiveness. Attrition is a pervasive challenge in obesity trials and real-world programs, often biasing outcomes and limiting long-term impact (23). The finding that over 85% of participants in the AI group met predefined adherence criteria suggests that algorithmic personalization and continuous feedback may enhance engagement beyond what can be achieved through intermittent human-delivered counseling. This is particularly relevant in resource-constrained settings, where access to multidisciplinary obesity care is limited and digital interventions may serve as force multipliers for existing healthcare infrastructure (24). However, these advantages are contingent on thoughtful implementation, including user-centered design and safeguards to ensure equitable access across varying levels of digital literacy. Despite these strengths, several limitations warrant consideration when interpreting the findings. The intervention duration, while sufficient to demonstrate short-term efficacy, does not allow assessment of long-term weight maintenance, which remains the ultimate challenge in obesity management (25). Behavioral adherence and engagement may attenuate over time, even with adaptive systems, and future studies should incorporate longer follow-up periods to evaluate durability of effect. Additionally, although the trial was adequately powered to detect moderate-to-large differences in primary outcomes, subgroup analyses were exploratory and may have been underpowered to detect effect modification by sex, baseline BMI, or socioeconomic status. These factors are known to influence both technology engagement and weight-loss trajectories and should be examined in larger, more diverse cohorts (26). Another consideration relates to the definition and transparency of “AI” within lifestyle interventions. While this study operationalized AI-driven personalization through algorithmic adaptation of goals and feedback based on continuous behavioral inputs, the broader literature remains heterogeneous in how AI is implemented and reported (27). Greater standardization in describing algorithmic logic, update frequency, and behavioral targets would improve reproducibility and facilitate comparison across trials. Moreover, although no adverse events related to the intervention were observed, ongoing evaluation of potential risks—such as excessive dietary restriction or technology-related burden—is essential, particularly as AI systems become more autonomous and widely deployed (28). In summary, the findings of this trial support the hypothesis that AI-driven personalized weight management can deliver clinically meaningful improvements in weight loss and adherence-related behaviors compared with standard counseling alone. By demonstrating large, consistent effects across anthropometric, behavioral, and metabolic domains, the study contributes robust randomized evidence to a field often characterized by heterogeneous and short-term evaluations. These results suggest that AI-assisted personalization may represent a valuable adjunct to conventional obesity care, particularly when designed to operationalize evidence-based behavior change techniques and integrated thoughtfully into existing healthcare pathways. Future research should focus on long-term maintenance, equity of access, and hybrid care models that combine algorithmic intelligence with targeted human support to maximize both effectiveness and sustainability (29)

## CONCLUSION

In conclusion, this randomized controlled trial provides robust evidence that an AI-driven personalized weight management intervention yields superior short-term outcomes in weight reduction, behavioral adherence, and metabolic health compared with standard counseling-based approaches among obese adults. The integration of adaptive, data-informed personalization was associated with larger and more consistent reductions in body weight and BMI, alongside meaningful improvements in physical activity, dietary adherence, self-monitoring behaviors, and cardiometabolic markers. These findings underscore the clinical value of leveraging artificial intelligence to enhance treatment fit, sustain engagement, and optimize behavior change mechanisms that underpin successful obesity management. While longer-term follow-up is required to determine durability of effects, the results support the role of AI-assisted personalization as a scalable, effective adjunct to conventional obesity care, particularly in resource-constrained settings where continuous human-delivered support is limited.

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## DECLARATIONS

**Ethical Approval**

Ethical approval was not required because this study was a narrative review of published literature and did not involve human/individual identifiable data.

**Informed Consent**

NA

**Conflict of Interest**

The authors declare no conflict of interest.

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**Authors' Contributions**

Concept: MA; Design: FSAOA; Data Collection: ZN, UA, NUN; Analysis: MZI; Drafting: MA, MAW

**Data Availability**

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

**Acknowledgments**

*Not applicable.*

**Study Registration**

Not applicable.