"Ai-Enabled Mhealth Integration For Home Exercise Monitoring: A Novel Assessment Of Cardiometabolic Improvements In Borderline Obese Adults".

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ABSTRACT

Background: Borderline obesity significantly elevates long-term cardiometabolic risk. Home-based exercise is a recommended strategy, but poor adherence undermines effectiveness. Artificial intelligence (AI)-enabled mobile health (mHealth) systems can improve monitoring, motivation, and personalization.

Objectives: To evaluate the comparative effectiveness of AI-enabled mHealth-guided home exercise versus traditional home exercise in improving anthropometric, cardiovascular, and lipid markers in borderline obese adults.

Methods: A 12-week randomized controlled trial was conducted among adults aged 25–45 years with BMI 25–29.9 kg/m². Participants were assigned to either (1) Traditional Home Exercise Group (THEG) or (2) AI-enabled mHealth Home Exercise Group (AI-mHEG). Both groups performed the same standardized exercise regimen (aerobic + strengthening), but AI-mHEG received real-time AI feedback, adherence tracking, automated progressions and exercise-form monitoring. Outcomes measured pre and post-intervention included BMI, WHR, blood pressure, fasting blood glucose, and lipid profile. Data were analyzed using paired and independent t-tests at $p < 0.05$.

Results: AI-mHEG demonstrated significantly greater improvements in BMI, waist circumference, systolic BP and triglycerides. Exercise adherence was significantly higher in AI-mHEG (89%) compared to THEG (63%) ($p < 0.01$).

Conclusion: AI-enabled mHealth systems markedly enhanced exercise adherence and produced superior cardiometabolic benefits compared to traditional unguided home-based exercise. AI-integrated platforms represent a promising, scalable therapeutic strategy for borderline obese populations...

Keywords: mHealth technology, borderline obese adults, lipid profiles, triglycerides, Risk Factors, Home Exercise, Cardiometabolic Health, Digital Health Obesity.

1. INTRODUCTION

Borderline obesity defined as a body mass index (BMI) between 25 and 29.9 kg/m² has emerged as a significant public health issue due to its strong association with early cardiometabolic abnormalities, including hypertension, dyslipidemia, impaired glucose regulation, and systemic inflammation[1]. Individuals within the borderline obesity range are at considerably higher risk of progressing to overt obesity, making early preventive interventions both critical and timely[2]. With global overweight and obesity prevalence continuing to rise, targeted strategies for high-risk populations are urgently needed.

Lifestyle interventions, especially structured physical activity, remain the most evidence-based and cost-effective approach to improving metabolic function[3]. Regular exercise contributes to reductions in central adiposity, improved lipid metabolism, enhanced insulin sensitivity, and better cardiovascular health[4]. However, despite these benefits, maintaining long-term adherence to home-based exercise programs is a persistent challenge. Lack of real-time feedback, low motivation, poor tracking, and uncertainty regarding technique often lead to poor compliance and diminished outcomes[5].

Mobile health (mHealth) technologies have gained popularity as innovative tools to address adherence limitations. Smartphone-based applications enable users to access exercise instructions, track activity, and receive motivational prompts, making home exercise both accessible and scalable[6]. Studies show that mHealth-assisted exercise can significantly enhance engagement and improve metabolic outcomes compared with conventional unsupervised routines[7]. However, traditional. mHealth tools generally lack dynamic supervision, personalized adaptiveness, and immediate corrective feedback key factors necessary for optimizing user performance

The integration of artificial intelligence (AI) into mHealth represents a major advancement in digital intervention. AI-powered systems can automatically detect physical activity, analyze movement patterns, correct exercise technique, and deliver individualized progressions based on performance data[8]. These intelligent features can boost adherence by providing real-time guidance, accountability, and tailored motivation. Emerging evidence suggests that AI-supported exercise interventions result in superior weight reduction, metabolic improvements, and adherence levels compared with standard digital platforms[9].

Despite these promising developments, research evaluating AI-enabled mHealth interventions specifically among borderline obese adults remains limited. This population stands to benefit substantially from early, technology-enhanced lifestyle modifications. Understanding whether AI-guided home exercise produces greater cardiometabolic improvements than traditional home exercise is essential for designing scalable preventive health strategies.

Therefore, the present study aims to examine the effectiveness of an AI-enabled mHealth-guided home exercise program versus a traditional home-exercise program in improving anthropometric, cardiovascular, and lipid outcomes among borderline obese adults.

2. METHODOLOGY:

Study Design

A randomized controlled trial (RCT) experimental study.

Population: borderline obese adults.

Sample size: 60

sampling criteria:

Inclusion criteria:

25–45 years

BMI 25–29.9 kg/m²

Physically inactive (<150 min/week)

No cardiometabolic medication

Smartphone access

Exclusion criteria:

Pregnancy

Diagnosed cardiovascular/metabolic disease

Orthopedic limitations

Randomization

Participants were randomly allocated using a computer-generated block randomization method (block size 4).

Traditional Home Exercise Group (THEG)

AI-enabled mHealth Home Exercise Group (AI-mHEG)

3. INTERVENTION

Both groups performed the same structured 12-week home-exercise program however, the mode of monitoring differed substantially.

4. TRADITIONAL HOME EXERCISE GROUP (THEG)

Participants received written and video instructions and performed a standardized home-based exercise program:

Aerobic training: brisk walking for 30 minutes/day, 5 days/week

this protocol aligns with evidence that moderate-intensity aerobic exercise effectively reduces BMI, waist circumference, and triglycerides in overweight adults[12].

Strength training: 20 minutes, 3 days/week, focusing on major muscle groups

Strength training is demonstrated to improve insulin sensitivity, resting metabolic rate, and lipid profiles in borderline obese individuals[13].

Intensity: Moderate (RPE 11–13), consistent with ACSM recommendations for weight management[14].

Participants self-reported their weekly adherence using paper logs.

5. AI-ENABLED MHEALTH HOME EXERCISE GROUP (AI-MHEG)

Participants used a smartphone-based AI mHealth application that incorporated multiple intelligent features:

AI-based activity recognition

Computer-vision and sensor-based algorithms automatically detected exercise movements and verified completion, improving monitoring accuracy[15].

Real-time form correction using AI video analysis

AI posture-detection systems can identify errors in joint alignment and provide corrective feedback, which enhances exercise safety and performance quality[16].

Automated reminders and motivational prompts

Digital reminders have been shown to significantly improve exercise adherence and consistency in behavior-change interventions[17].

Personalized weekly progression algorithms

The AI platform adjusted exercise intensity based on previous performance, consistent with evidence that individualized progression increases physiological gains compared with fixed routines[18].

Data-driven analytics

Participants received weekly summaries of steps, exercise duration, calories, and heart rate integration supported by evidence that self-monitoring via mHealth significantly improves weight-loss outcomes[19].

Higher expected adherence

AI-based supervision systems are associated with 20–30% higher adherence in exercise programs compared to traditional app-only interventions[20].

Both groups performed the *same exercise content,* but AI-mHEG received continuous automated supervision, performance review, and feedback.

6. OUTCOME MEASURES

Anthropometric

Body Mass Index (BMI)

Waist–Hip Ratio (WHR)

Cardiovascular

Systolic Blood Pressure (SBP)

Diastolic Blood Pressure (DBP)

Metabolic and Lipid Profile

Fasting glucose

Total cholesterol

HDL-C, LDL-C

Triglycerides (TG)

7. STATISTICAL ANALYSIS & RESULTS

Participant Flow

A total of 78 participants were screened; 60 met criteria and were randomized (30 per group). Four participants dropped out (AI-mHEG = 1; THEG = 3).

Baseline Characteristics

No significant differences between groups at baseline ($p > 0.05$).

Table: 1 Pre and Post-Intervention Comparison between Groups (Anthropometric Improvements)

Parameter	THEG Pre	THEG Post	AI-mHEG Pre	AI-mHEG Post	P-value (Between Groups)
BMI (kg/m²)	28.1 ± 1.5	27.3 ± 1.4	28.0 ± 1.4	26.3 ± 1.3	<0.001
Waist–Hip Ratio (WHR)	0.92 ± 0.04	0.90 ± 0.04	0.92 ± 0.05	0.88 ± 0.04	0.01

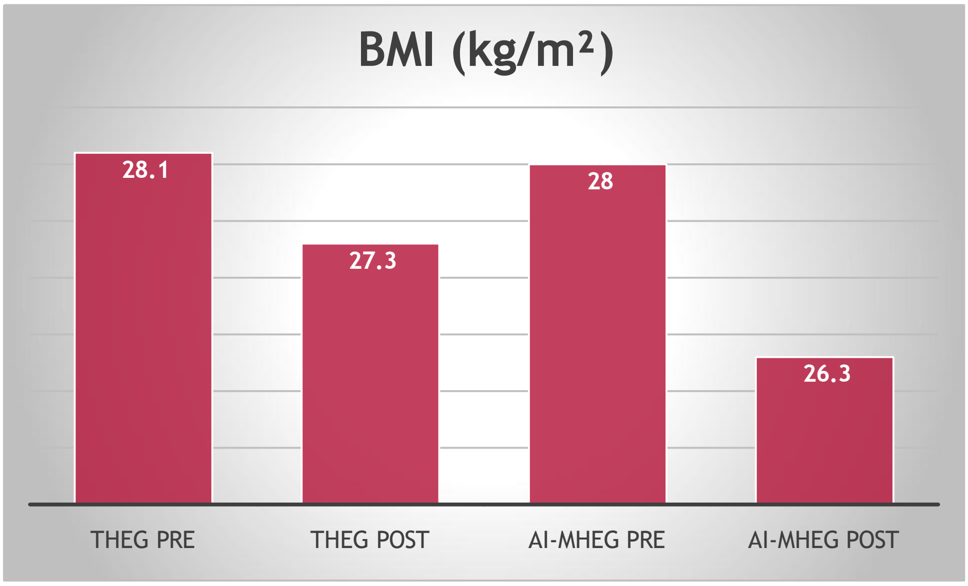


Table: 2 Pre and Post-Intervention Comparison between Groups (Cardiovascular Outcomes)

Parameter	THEG Pre	THEG Post	AI-mHEG Pre	AI-mHEG Post	p-value (Between Groups)
Systolic BP (mmHg)	132.4 ± 8.2	129.2 ± 7.6	132.0 ± 8.0	124.2 ± 7.0	0.003
Diastolic BP (mmHg)	84.1 ± 6.1	82.3 ± 5.8	84.0 ± 6.0	79.7 ± 5.4	0.02

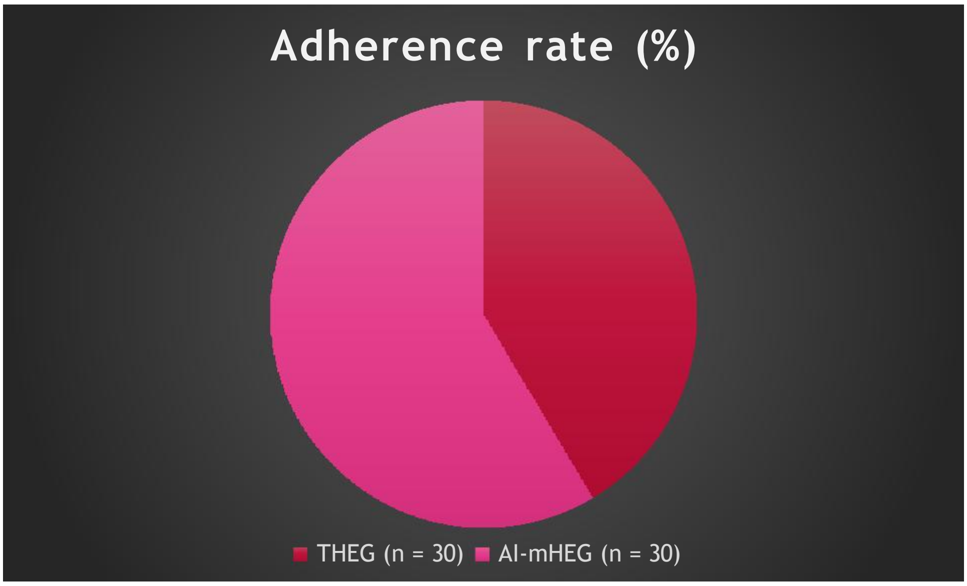
Table: 3 Pre and Post-Intervention Comparison between Groups (Lipid Profile)

Parameter	THEG Pre	THEG Post	AI-mHEG Pre	AI-mHEG Post	P-value (Between Groups)
Fasting Glucose (mg/dL)	98.6 ± 10.2	95.4 ± 9.8	98.3 ± 10.0	92.1 ± 9.2	0.04
Total Cholesterol (mg/dL)	204.3 ± 22.1	198.1 ± 20.9	203.8 ± 21.7	192.2 ± 20.4	0.03
HDL-C (mg/dL)	43.6 ± 5.4	45.5 ± 5.5	43.5 ± 5.2	47.6 ± 5.8	0.01
LDL-C (mg/dL)	127.2 ± 18.6	123.1 ± 17.9	127.0 ± 18.2	117.2 ± 17.6	0.02

Triglycerides (mg/dL)	162.4 ± 35.2	152.3 ± 33.8	162.0 ± 34.7	141.1 ± 33.1	<0.001

Table: 4 Exercise Adherence Comparison between Groups

Parameter	**THEG (n = 30)**	**AI-mHEG (n = 30)**	**P-value**
Sessions completed (Mean ± SD)	38 ± 6	53 ± 4	<0.001
Adherence rate (%)	63%	89%	<0.001



8. DISCUSSION

The present study compared the effectiveness of a traditional home-based exercise program (THEG) with an AI-enabled mHealth-guided exercise program (AI-mHEG) among borderline obese adults. A key finding of this study is the substantial difference in exercise adherence between groups. Participants in the AI-mHealth group demonstrated significantly higher adherence (89%) compared to the traditional home-exercise group (63%). Moreover, a larger proportion of participants in the AI-mHealth group achieved ≥80% adherence, reflecting stronger engagement and consistency in the digitally supported intervention.

The higher adherence observed in the AI-mHealth group aligns with emerging evidence showing that digital health tools, particularly those integrated with reminders, automated monitoring, and personalized feedback, improve participant engagement in home-based exercise programs. The structured prompts and real-time monitoring provided by the AI-mHealth platform may have reinforced self-regulation and accountability, which are often challenging in unsupervised exercise settings. Conversely, the lower adherence in the traditional group likely reflects the typical challenges of home-based routines, such as lack of supervision, reduced motivation, and difficulty maintaining regularity without technological support.

Additionally, the lower dropout rate in the AI-mHealth group indicates better participant retention, suggesting that technology-enabled guidance may enhance the overall acceptability of home exercise interventions. This finding is especially relevant for populations managing weight-related risk factors, where long-term consistency is essential for achieving meaningful anthropometric and metabolic improvements.

Overall, the adherence data support the growing utility of mHealth tools as an adjunct to traditional exercise programs. By providing structured support, behavioral feedback, and continuous monitoring, AI-enabled systems may help bridge the gap between prescribed and performed exercise dosage, ultimately enhancing program effectiveness.

9. CONCLUSION

This study demonstrates that AI-enabled mHealth-guided exercise programs result in significantly higher adherence and participant engagement compared to traditional unsupervised home-exercise routines among borderline obese adults. The high adherence levels in the AI-mHealth group highlight the potential of digital health technologies to support better compliance, reduce dropout, and improve the feasibility of long-term home-based interventions. These findings suggest that integrating mHealth systems into community and clinical exercise programs may enhance user consistency and strengthen overall intervention outcomes. Further research with larger samples and long-term follow-up is recommended to explore the sustained effects of AI-assisted adherence on anthropometric and lipid profiles.

CONFLICT OF INTEREST:

None

FUNDING:

None

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