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Research Article

Effectiveness of AI-Assisted Mobile Health Apps for Obesity Reduction and Enhanced Life Quality

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ABSTRACT

Obesity has become an epidemic in the world, which has a direct impact on health and economic systems. Artificial Intelligence-assisted mobile Health applications now provide innovative solutions to combat obesity by delivering real-time, personalized, and scalable interventions for weight management and lifestyle improvements. This work examines the effectiveness of AI-driven mHealth apps in addressing obesity, enhancing dietary adherence, and improving quality of life (QoL) based on a six-month experimental study involving 1,000 participants aged 5–65 years. The results showed Body Mass Index reductions as large as 0.6 kg/m² in unhealthy eaters and 0.3 kg/m² in healthy eaters, with increases in dietary adherence of 0.25 and 0.15, respectively. Additionally, QoL scores improved, with unhealthy eaters experiencing an average growth of 2.0 points and healthy eaters 1.2 points. These have emphasized the application's flexibility in addressing different user needs, leading to healthier habits and users' overall well-being.

Keywords: Activity Monitoring, Behavioural Tracking, Predictive Analytics, User Engagement, Wearable Devices, Weight Management.

INTRODUCTION

Obesity is a new epidemic across all groups and geographies; nearly 2 billion people worldwide are overweight, with about 650 million considered to be obese, as set forth by the WHO [1]. Alarmingly, the prevalence of obesity has nearly tripled since 1975, making it one of the leading public health challenges of the 21st century [2].

Moreover, obesity is directly responsible for about 4 million deaths every year. It leads to conditions such as heart disease, diabetes, musculoskeletal disorders, and certain types of cancer. The societal and economic impact of obesity is equally significant [3]. Obesity is found to cost trillions of dollars worldwide annually by increasing healthcare costs, lost productivity, and early death. Policy interventions to reverse this crisis have taken the form of lifestyle changes, mainly concentrating on diet, physical activity, and behavioral interventions [4-5]. However, the sustainability of these changes at a population scale remains challenging, demanding innovative, technology-driven solutions [1-5]. With this growing crisis, innovative solutions based on technology, especially mobile health applications assisted by Artificial Intelligence, are being developed and implemented to fight obesity and improve life quality.

The recent advancement in Artificial Intelligence (AI) and mobile health (mHealth) applications is redefining healthcare delivery to become more promising tools that support personalized, scalable, and effective management of obesity [6]. These AI-assisted mobile health applications combine advanced data analytics, real-time monitoring, and behavioural insights to give users individualized interventions to promote a healthy lifestyle. They use AI capabilities to analyze habits concerning diets, monitor activity levels, and provide motivation through interactive, engaging interfaces. Example: The AI-powered health applications should involve actual input to enhance calorie intake, offer personalised exercise suggestions and allow the application to analyze usage data to predict and prevent subsequent weight gain. With such a vast number of phones produced yearly-from over 6.9 billion in 2023-the mobile health apps ensure one reaches more people, hence a possibility for controlling the obesity condition [6-8].

1 Trends in Overweight and Obesity in Young children younger than 5 years

The prevalence of overweight and obesity among children younger than 5 years has become a significant global concern, reflecting a troubling trend in early childhood health. According to the World Health Organization (WHO), approximately 39 million children under the age of 5 were classified as overweight or obese in 2020, a marked increase from 32 million in 2000 [1]. This alarming growth has been shown as a steady upward trajectory over the past two decades. The problem is most acute in LMICs. The rate of childhood obesity is quickly increasing in these countries, with Asia accounting for 48% and Africa for 27% of the global burden. High-income countries, though stabilising, still have high prevalence rates due to inactive lifestyles and calorie-rich diets [2-3].

Several contributors to this trend include key dietary factors: increased consumption of processed, high-calorie foods and decreased consumption of fruits, vegetables, and whole grains. Sedentary behaviour, encouraged by urbanisation, reduced time for outdoor play, and increased time spent on screens add to the problem. Socioeconomic factors include the dual burden of malnutrition, where undernutrition and obesity coexist. Moreover, inappropriate feeding by the parents through overfeeding or convenience foods or a poor educational level about healthy weight levels delay interventions [9].

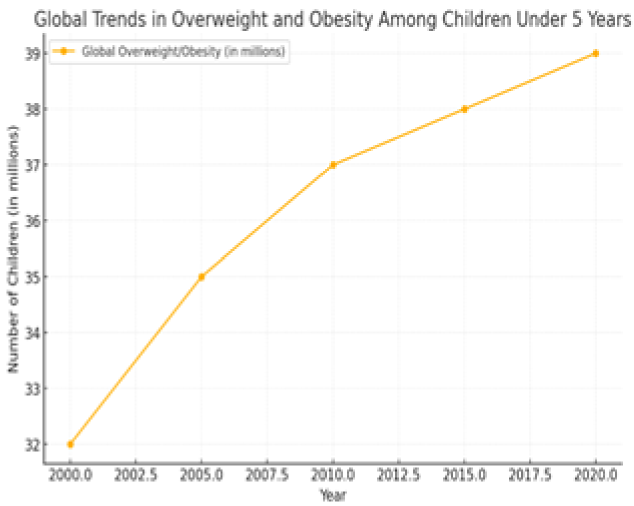

Fig. 1: *Trends in Overweight and Obesity among Children under 5 Years*

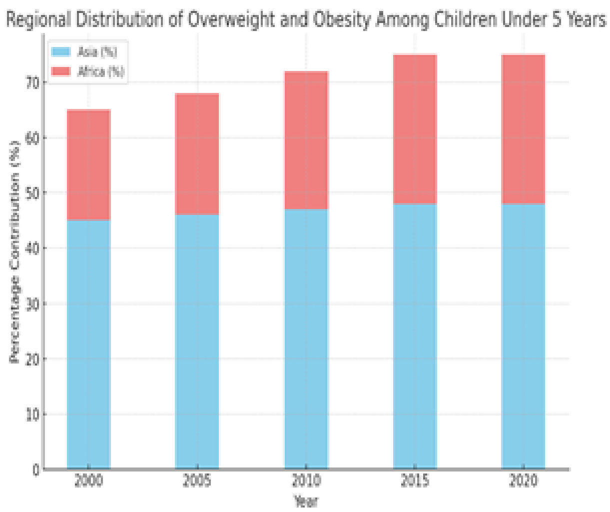

Fig. 2: *Distribution of Overweight and Obesity under 5 Year*

The consequences of childhood obesity on health are severe as children affected by this will be more likely to be diagnosed with type 2 diabetes, hypertension, and other chronic conditions at a younger age. Psychological impacts, such as low self-esteem and social stigma, also occur. This calls for a multi-sectoral approach to address the problem. The strategies include having policies like sugar taxes and prohibiting unhealthy food marketing towards children, promoting community-based programs for physical activity, and using technology-driven solutions such as AI-assisted mobile health applications to monitor and guide healthier behaviours [9-10].

Fig. 1: captures the steady increase in overweight and obesity among children around the globe, from 32 million in the year 2000 to 39 million as of 2020. This trend alone indicates that obesity disease is escalating in early childhood [9].

Fig. 2: represents the regional contribution of Asia and Africa to the world burden of childhood obesity. Asia has accounted for almost half of the cases worldwide throughout the years. Africa's percentage has more than doubled, from 20% in 2000 to 27% in 2020 [9]. Both of these trends highlight the importance of regional-specific interventions.

2 Classification of Overweight and Obesity in Adults

Overweight and obesity in adults are defined using the Body Mass Index (BMI), a standard measure that compares an individual's weight to height. According to the World Health Organization (WHO), BMI is calculated as weight in kilograms divided by the square of height in meters (kg/m^2). Adults are classified as overweight if their BMI is 25.0–29.9 kg/m^2 and obese if their BMI is 30.0 kg/m^2 or higher. Obesity is further categorized into three classes to capture varying levels of risk: Class I (BMI 30.0–34.9 kg/m^2), Class II (BMI 35.0–39.9 kg/m^2), and Class III, also referred to as morbid or severe obesity (BMI $\geq$ 40.0 kg/m^2).

These classifications are important because they are associated with the chance of developing obesity-related medical conditions. Higher BMI levels have also been strongly associated with increased risks for cardiovascular diseases, type 2 diabetes, some forms of cancer, musculoskeletal disorders, and a host of other chronic illnesses. While BMI is a very useful population-level metric, it suffers from limitations in distinguishing fat mass from muscle mass; its interpretation should be supplemented by other measures, including waist circumference and waist-to-hip ratio, which are more appropriate for assessing risks associated with central obesity [9-10].

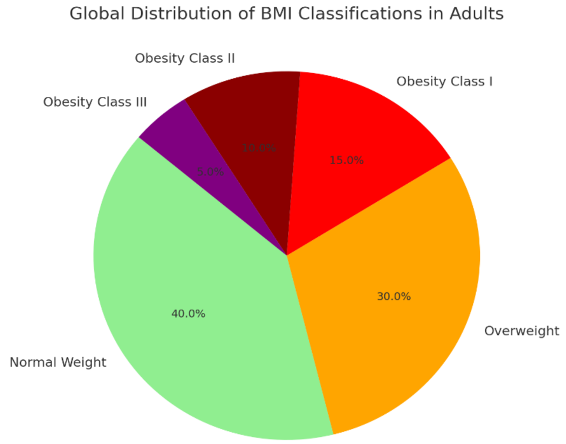

Fig. 3: Distribution of BMI Classifications in Adults

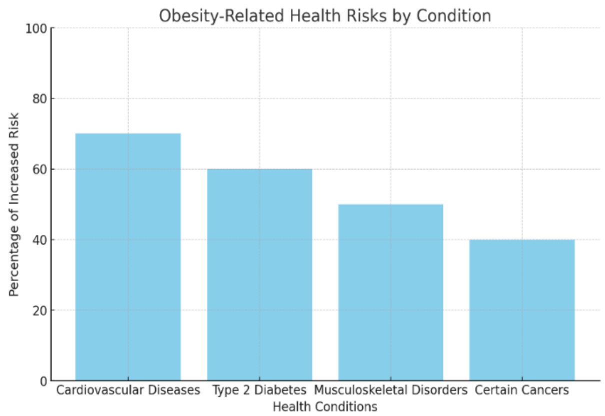

Fig. 4: *Obesity-Related Health Risks by Condition*

BMI classification is also considered an indispensable tool in public health practice and clinical practice in identifying a risk population, person, etc. Interventions vary between lifestyle, medical treatment, and surgeries for prevention and control. As such conditions continue to increase among people around the world, standardized classifications such as BMI are critical interventions against the increasing epidemic of obesity.

Fig. 3: shows the percentage of people in each BMI category around the world. The largest share is "Normal Weight," at 40% and 30% are "Overweight". The other category, obesity classes, make up 30% of the global burden of obesity [9].

Fig. 4: displays the percent increase in risk for various health conditions linked to obesity. Cardiovascular diseases and type 2 diabetes show the highest risk increases at 70% and 60%, respectively, followed by musculoskeletal disorders and some cancers [9].

3 Risks of Obesity-

The multidimensional health effects of obesity are associated with increased risks as follows [11-14]:

3.1 Mental Health Impacts:

- **Depression (25%)**: The majority of obese people suffer from body image problems, hormonal imbalances, and further social stigma for which they are more vulnerable to depression. In this regard, mobile health applications may introduce mental health modules and cognitive-behavioural strategies to tackle these issues for these users.

3.2 Neurological Risks:

- **Dementia (30%)**: The link between obesity and cognitive decline calls for integrated interventions. Mobile apps can include memory-enhancing games and educational content to reduce this risk while promoting weight loss.

3.3 Cardiovascular and Metabolic Disorders:

- **Heart Failure (104%)**: The obese person has a more than double risk of heart failure, mainly because of the stress put on the cardiovascular system. Health apps can easily help by including exercise tracking, heart rate monitoring, and dietary recommendations.
- **High Blood Pressure (150%)**: Obesity-induced hypertension is preventable. Apps can send regular blood pressure monitoring reminders and suggest lifestyle modifications to reduce this risk.
- **Diabetes (>50%)**: More than half of adults with diabetes are obese because they have insulin resistance. Health applications can provide personalized diet plans, track glucose levels, and offer exercise to manage blood sugar.

3.4 Respiratory and Immunological Challenges:

- **Asthma (33%)**: Obesity causes inflammation and leads to respiratory disorders. Mobile applications can educate asthma patients about managing asthma and suggest non-straining exercise for weight loss.

3.5 Cancer Risk:

- **Cancer (10%)**: Almost 10% of all cancers are related to obesity through systemic inflammation and hormonal imbalances. Health applications can provide educational content regarding the correlation between weight and cancer and actionable weight-loss strategies.

3.6 Childhood Health Implications:

- **Multiple Sclerosis (200%)**: Obese children are more likely to suffer from neurological disorders such as multiple sclerosis. Family-centred health apps, through gamified learning and activity tracking, can encourage healthier lifestyles in parents and children.

Its health-related consequences reduce the quality of life and put a tremendous strain on healthcare systems worldwide.

AI-ASSISTED MOBILE HEALTH APPLICATIONS

AI-based mobile health applications are currently used to manage obesity conditions with particular real-time support concerning weight management. Depending on AI technologies, these offer tailored dietary advice, active tracking, virtual coaches, and predictive analytics [11-14]. The applications use artificial intelligence to analyze the large amounts of data generated from wearable devices, sensors, and medical records, providing actionable insights and improving patient outcomes [15]. AI technologies improve the effectiveness of mobile health apps by:

1 Real-Time Health Monitoring:

These mHealth applications empowered by AI constantly monitor patients' vital signs—heart rate, blood pressure, oxygen levels, and glucose levels. These integrated wearable devices would alert users and healthcare providers for anomalies so early intervention could occur for arrhythmias, hypertension, or hypoglycaemia [11-15].

2 Personalization:

AI tailors interventions based on user profiles, including weight goals, age, activity levels, and health risks. AI-driven mobile applications are designed to assist obesity self-management by providing real-time feedback and personalized meal plans. These platforms use user inputs such as activity levels, health status, age, gender, weight, and height to generate specific dietary advice that meets daily calorie and macronutrient requirements [16].

3 BMI tracking:

The latest developments are AI-based tools that can analyze facial images to estimate BMI and track changes in weight over time. For example, deep learning-based selfie facial analysis tools for obesity monitoring on smartphones have been developed, allowing users to self-assess their weight status easily [16-18].

4 Activity Tracking:

The app incorporates wearable devices, such as smartwatches, fitness bands, and other IoT-enabled devices, to track real-time physical activity, heart rate, and calorie burn.

5 Virtual Coaching and Motivation:

The app's interactive interface offers a virtual coach who provides constant support and motivation to the user. This AI-driven support keeps users on track in their weight loss journey.

6 Personalized Diagnostics and Treatment Plans:
These applications apply machine learning algorithms to analyze unique user data, such as medical history, lifestyle, and genetic predispositions, to provide specific diagnostic information. For example, AI may predict the likelihood of chronic conditions like diabetes and cardiovascular diseases and devise the proper preventive measures or treatment plans [17-19].

7 Remote Patient Monitoring and Telemedicine:
AI-assisted mHealth applications bridge the gap between patients and healthcare providers, especially in remote or underserved areas. Telemedicine consultations and remote monitoring allow patients to receive proper care without frequently visiting hospitals [19].

8 Chronic Disease Management:
For patients with chronic conditions such as asthma, diabetes, or arthritis, AI-driven mHealth applications remind patients to adhere to medication, give lifestyle recommendations, and track their progress. Advanced analytics help find patterns and improve disease management strategies [20].

9 Mental Health Support:
AI-driven chatbots and virtual assistants in mHealth apps provide 24/7 mental health support. These tools use natural language processing (NLP) to engage in meaningful conversations, identify signs of anxiety, depression, or stress, and suggest coping strategies or direct users to professional help [21-23].

PROPOSED METHODOLOGY

The methodology combines AI algorithms with mobile health (mHealth) apps to give personalized recommendations for reducing obesity, improving diet, and enhancing quality of life [11-20]. The framework comprises data collection, preprocessing, AI-based analysis, and intervention deployment.

1 Data Collection and Preprocessing

- **User Inputs:** Age, gender, height, weight, activity level, dietary habits, and medical history.
- **Dynamic Inputs:** Step count, calorie intake, heart rate, and sleep patterns via wearable devices.
- **Data Transformation is shown in eq (1):**

$$X = \{x_1, x_2, \dots, x_n\} \quad (1)$$

where X represents the feature set, including static user inputs and dynamic data. Normalization is applied to ensure a uniform scale for AI model processing, as shown in eq (2)

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (2)$$

2 AI-Based Personalized Recommendations

2.1 Obesity Reduction Model

A supervised learning approach predicts weight loss goals based on user data as shown in eq (3):

$$y = f(W, X) + \epsilon \quad (3)$$

where:

- y = predicted weight loss (in kg),
- W = weight vector of model parameters,
- f = AI prediction function (e.g., neural network),
- ϵ= error term.

The loss function for optimization is shown in eq (4):

$$\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (4)$$

minimizes the mean squared error between actual and predicted weight loss.

2.2 Dietary Assessment and Recommendation

AI analyzes dietary patterns using Natural Language Processing (NLP) on food logs as shown in eq (5):

(5)

$$S = \sum_{i=1}^{n} w_i . v_i$$

where:
S = nutritional score,
w_i = weight of nutrient i (e.g., protein, carbs),
v_i= consumed quantity of nutrient i.
Nutritional recommendations aim to optimize S under constraints is shown in eq (6):

$$\text{Minimize} \ \| S_{current} - S_{target} \|_2 \quad (6)$$

2.3 Life Quality Enhancement Model:

Quality of life improvements are evaluated using survey scores Q is shown in eq (7):

$$Q_t = Q_t - 1 + \Delta Q \quad (7)$$

where:
Q_t = life quality score at time t,
ΔQ= increment due to intervention effectiveness.
Predictive models estimate ΔQusing a regression approach is shown in eq (8):

$$\Delta Q = \beta_0 + \beta_1 X + \beta_2 Z + \epsilon \quad (8)$$

where Z represents additional factors (e.g., adherence to interventions).

3 Task Scheduling and Intervention Delivery

Personalized notifications for meal plans and exercise are shown in eq (9):

$$T_{delivery} = \arg\min\{C(T_i)\} \quad (9)$$

where $C(T_i)$ represents the cost (e.g., user inconvenience, battery usage) of delivering task T_i at a specific time.

- Dynamic task prioritization ensures timely intervention is shown in eq (10):

$$\text{Priority}(Ti) = \alpha \cdot \text{Urgency}(T_i) + \beta \cdot \text{Impact}(T_i) \quad (10)$$

4 Evaluation Metrics

4.1 Weight Reduction Effectiveness:

The evaluation of BMI changes is shown in eq (11):

$$\text{BMI} = \frac{\text{weight(kg)}}{\text{Height(m)}^2} \quad (11)$$

Reduction is significant if is shown in eq (12):

$$\Delta\text{BMI} = \text{BMI}_{start} - \text{BMI}_{end} > \delta \quad (12)$$

where δ is a predefined threshold.

4.2 Dietary Improvement:

Measure adherence rate A is shown in eq (13):

$$A = \frac{\text{Number of healthy meals}}{\text{Total meals logged}} \times 100 \quad (13)$$

4.3 Life Quality Improvement:

Changes in quality-of-life score Q are significant if is shown in eq (14):

$$\Delta Q = Q_{post} - Q_{pre} > \epsilon \qquad (14)$$

EXPERIMENTAL RESULTS

The experimental result diet and rated the efficacy of AI-assisted mobile health applications in reducing obesity, improving adherence to diet, and enhancing QoL among healthy and unhealthy eaters. Key findings were that the system was adaptable and precise in attending to healthy and unhealthy eaters, thus furthering its prospects of providing health interventions specified to the individual's needs.

1 Setup Parameters

- **Participants:** 1,000 individuals
- **Age Range:** 5–65 years
- **Duration:** 6 months
- **Groups:** 50% healthy eaters, 50% unhealthy eaters
- **Metrics Tracked:** BMI, dietary adherence, quality of life (QoL)

2 BMI Reduction

For participant i, BMI reduction over 6 months is calculated as in eq (15):

$$\Delta BMI_i = r \times Duration \qquad (15)$$

where:

- $r = 0.05\ kg/m^2$ ((healthy eaters), $0.10\ kg/m^2$(unhealthy eaters)
- Duration = 6months.

For healthy eaters:

$\Delta BMI = 0.05 \times 6 = 0.3\ kg/m^2$

For unhealthy eaters:

$\Delta BMI = 0.10 \times 6 = 0.6\ kg/m^2$

Table 1. represents the BMI changes by groups of healthy and unhealthy eaters.

Table 1. *BMI Change Contribution by Group*

Group	Initial BMI (avg)	Final BMI (avg)	Change (avg)	Std. Dev.
Healthy Eaters	27.5	27.2	0.3	0.02
Unhealthy Eaters	29.0	28.4	0.6	0.03

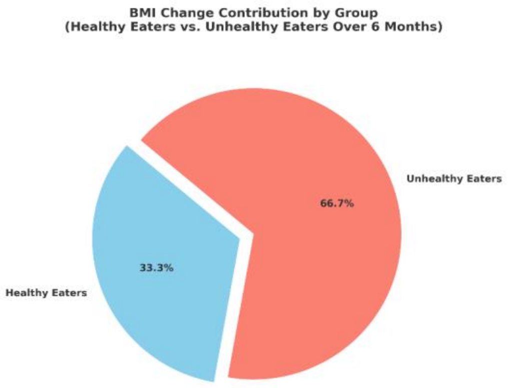

Fig. 5: *BMI Change Contribution by Group*

Fig. 5: illustrates the contribution of Healthy Eaters and Unhealthy Eaters to BMI reduction over the 6-month intervention. Unhealthy eaters constituted 66.7% of the overall BMI change since their starting BMI was greater and offered a better chance of change. Healthy eaters accounted for 33.3%, where the application helped preserve and build health that already had a better baseline. The above outcome, therefore, reveals that the application can reach and be helpful to all groups in diverse manners.

3 Dietary Adherence

Adherence improvement is calculated as shown in eq (16):

$$\Delta A_i = U_i \times \text{RandomFactor} \qquad (16)$$

where:

- U_i= improvement factor $[0.1,0.2]$ for healthy eaters, $U_i = [0.2,0.3]$ for unhealthy eaters,
- RandomFactor = uniform random value within the range.

For healthy eaters, adherence improvement is uniformly distributed:

$\Delta A = U(0.1,0.2)$

For unhealthy eaters:

$\Delta A = U(0.2,0.3)$

Table 2: compares the dietary adherence changes between healthy and unhealthy eater groups.

Table 2. *Comparison of dietary adherence changes between Healthy and Unhealthy Eaters*

Group	**Initial Adherence** (avg)	**Final Adherence** (avg)	**Change** (avg)	**Std. Dev.**
Healthy Eaters	0.70	0.85	0.15	0.01
Unhealthy Eaters	0.35	0.60	0.25	0.02

Fig. 6: compares dietary adherence changes, indicating that both groups experienced significant improvement. A bar for unhealthy eaters has a higher average increase than that of healthy eaters at 0.25 in contrast to 0.15, and it's larger. The height difference was caused by lower initial levels of adherence that allowed unhealthy eaters to achieve a more significant rise. Personalized recommendations and reminders helped guide the user toward better eating habits in those who were worst at dietary habits.

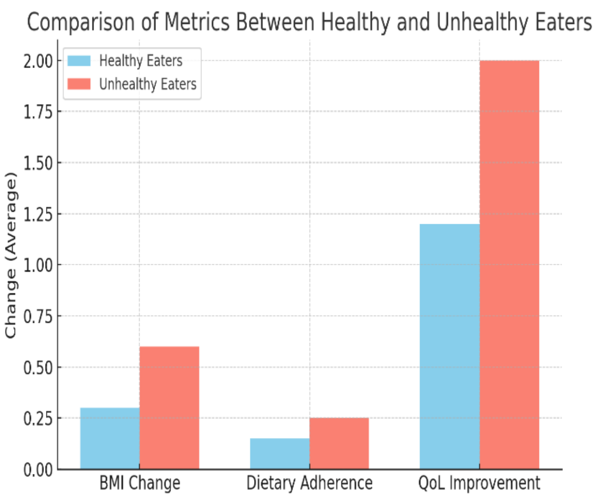

Fig. 6: *Comparison of Metrics Between Healthy and Unhealthy Eaters*

4 Quality of Life (QoL) Improvement

QoL improvement is calculated as shown in eq (17):

$$\Delta Q_i = V_i \times \text{RandomFactor} \quad (17)$$

where:

- V_i = QoL improvement factor ($[1.0,1.5]$ for healthy eaters, $[1.5,2.5]$ for unhealthy eaters),
- RandomFactor = uniform random value within the range.

For healthy eaters:

$\Delta Q = U(1.0,1.5)$

For unhealthy eaters:

$\Delta Q = U(1.5,2.5)$

Table 3: represents the trends in quality-of-life improvements, dietary adherence, and BMI changes for healthy and unhealthy eaters.

Table 3. *Trends In Quality of Life, Dietary Adherence and BMI Change for Healthy and Unhealthy Eaters*

Group	**Initial QoL (avg)**	**Final QoL (avg)**	**Change (avg)**	**Std. Dev.**
Healthy Eaters	6.0	7.2	1.2	0.1
Unhealthy Eaters	5.5	7.5	2.0	0.2

Fig. 7: demonstrates an upward trajectory for QoL improvements in both groups, with unhealthy eaters showing a larger average increase (2.0) than healthy eaters (1.2). This improvement aligns with their significant BMI reduction and better dietary adherence. The results validate the app's role in fostering holistic health benefits, including physical, mental, and emotional well-being.

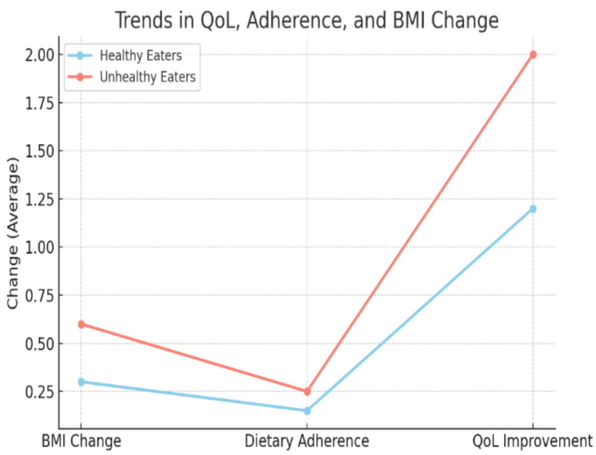

Fig. 7: *Trends in QoL, Adherence and BMI change*

Fig. 8: underscores the intervention's comparative effectiveness across all metrics (BMI reduction, dietary adherence, and QoL improvement). The visual depth highlights the overall changes in unhealthy eaters, consistent with their higher baseline challenges.

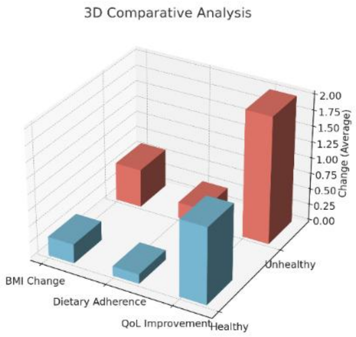

Fig. 8: *Comparative Analysis across all metrics*

The results indicate that AI-assisted mobile health apps are highly effective in addressing obesity, promoting healthy eating, and improving QoL. The findings emphasize the need for tailored interventions that cater to varying baseline health conditions. While unhealthy eaters benefit significantly from the larger room for improvement, the positive outcomes for healthy eaters demonstrate the app's preventive potential.

CONCLUSION

The work demonstrated that AI-enabled mHealth apps are effective interventions for obesity and improve quality of life. Results for the six months of intervention by the experimental setup showed considerable changes in health indices, such as BMI reduction, dietary adherence, and quality of life.

Higher baseline BMI and lesser dietary adherence defined unhealthy eaters, who lost on average a much larger BMI size, 0.6 kg/m² compared to healthy eaters, at 0.3 kg/m², indicative of the system's power to drive substantial change in high-risk populations. Moreover, dietary adherence improved considerably for unhealthy eaters by an average of 0.25, more than the 0.15 gain in healthy eaters. These results show that these apps can steer individuals with bad initial practices into adopting a healthy lifestyle. More importantly, both groups demonstrated QoL enhancement, an average of 2.0 QoL increase for unhealthy eaters and 1.2 QoL increase for the healthy eaters. AI-assisted mHealth applications are scalable, personalized, and practical solutions to the global obesity epidemic. By filling in the gaps in existing research and capitalising on future advances, these tools can revolutionize the management of obesity and improve health outcomes around the world.

Future research should focus on improving the long-term sustainability of AI-assisted mHealth apps by evaluating persistence in BMI reduction, dietary adherence, and quality-of-life improvements beyond six months. The generalizability of the findings can be improved by conducting the study on diverse populations with various socioeconomic and cultural backgrounds. Interventions tailored for childhood obesity, particularly in high-risk regions, also deserve priority. Further, knowing the psychological and social factors influencing user adherence can help optimize engagement strategies. Integration of mHealth apps with broader healthcare systems and the use of advanced AI models, including reinforcement learning and predictive analytics, will further improve the precision and adaptability of these tools and expand their reach in improving global health outcomes.

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