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Development of a personalized cardio exercise and diet tracking mobile application: CardioFit IOS

Yaren Uyan[1], Fatih Sarısoy*[2], Büşra Yılmaz[3], Harun Jira[4]
[1]Department of Computer Engineering, Faculty of Technology, Gazi University, Ankara, Turkiye
[2]Personal Trainer, Grand National Assembly of Turkiye, Ankara, Turkiye
[3]Department of Physical Education and Sport, Faculty of Sport Sciences, Gazi University, Ankara, Turkiye
[4]Kahramanmaraş Metropolitan Municipality Secondary School, Ministry of Education, Kahramanmaraş, Turkiye

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ABSTRACT

Aims: This study emphasizes the urgent need for integrated and adaptive platforms in the growing mobile health sector and aims to consolidate them into a common mobile platform. The main goal was to develop CardioFit IOS, an innovative IOS app designed to overcome limitations in existing mHealth tools. It provides a comprehensive, personalized health management platform that promotes sustainable healthy behaviors and user goal achievement.

Methods: Developed as a native IOS app using Swift and Firebase for secure data management and authentication, CardioFit IOS features an adaptive personalization engine powered by K-Means clustering. The engine analyzes user physiological data and in-app activities to form clusters, generating and refining personalized exercise, nutrition, and hydration plans beyond standard advice. It also includes real-time tracking of daily physical activity, diet, and water intake.

Results: CardioFit IOS unifies multiple health monitoring features into a single intuitive interface, improving user satisfaction by eliminating the need for multiple apps. Its AI-driven personalization via dynamic clustering delivers wellness strategies responsive to evolving user data, boosting engagement through continuous monitoring, feedback, and progress visualizations to enhance adherence to healthy routines.

Conclusion: CardioFit IOS represents a significant advance in mHealth, blending seamless integration with intelligent personalization. By leveraging advanced clustering and robust infrastructure, it supports users in achieving health and fitness goals, underscoring adaptive AI's value in personalized digital health interventions.

Keywords: Diet, firebase, fitness, healthy life, IOS, swift

INTRODUCTION

The pervasive integration of mobile phones and applications into daily life has propelled the popularity of fitness and healthy living apps. Research shows that mobile health (mHealth) applications effectively encourage physical activity and healthy dietary habits, leading to improved health outcomes and greater patient engagement (Basto & Ferreira, 2025; Pradal-Cano et al., 2020). These platforms are increasingly recognized as accessible, scalable solutions for promoting behavior change and managing chronic conditions (Ridwan et al., 2025).

Despite their widespread adoption and potential, many existing mHealth apps suffer from fragmentation and poor integration (Eaton et al., 2024; Mescher et al., 2024). Users often juggle multiple apps to track aspects of their health-such as exercise, diet, and hydration-resulting in a disjointed, inefficient experience. This fragmentation undermines adherence and long-term engagement, as evidenced by high dropout rates (Blasiak et al., 2022; Mazéas, 2023). Moreover, current systems rarely integrate diverse health data modalities, limiting holistic insights and personalized recommendations (Gougeh & Žilić, 2024; Smith et al., 2025).

To address these limitations, CardioFit IOS's provides an innovative, comprehensive solution with a fully integrated user experience (Susaiyah et al., 2024). It consolidates essential health and fitness tracking-dietary intake, hydration, and physical activity-into a single platform, eliminating the need to manage multiple apps (Zahedani et al., 2023). This approach aligns with growing interest in personal health monitoring systems that aggregate data from various sources to deliver real-time alerts, comprehensive tracking, and tailored insights (Mahato et al., 2024; Secara & Hordiiuk, 2024).

Beyond simple integration, CardioFit IOS evaluates collected data holistically, adapting to each user's daily context. It surpasses conventional multi-module apps by generating fully personalized plans aligned with individual lifestyles and health goals (Moz et al., 2023). Such personalization is key to boosting user engagement and mHealth effectiveness, ultimately enhancing motivation and sustaining healthy habits.

Corresponding Author: Fatih Sarısoy, fatihsarisoy08@gmail.com

Related Work & Motivation

A survey of mobile health applications in the literature reveals that CardioFit IOS core modules exercise tracking, water intake, and diet logging are present individually across various apps. However, no existing application integrates all three into a unified framework tailored to the individual user. While CardioFit IOS incorporates similar functions to those in current apps, it innovatively redesigns their interplay.

Most applications deliver these modules separately, requiring users to switch between apps to track exercise in one, log water intake in another, and record diet in a third. This fragmentation undermines practicality and long-term adherence. CardioFit IOS stands out not only by consolidating these features but also by interconnecting the data and adapting it to users' daily contexts, surpassing conventional multi-module apps. Moreover, it offers a free trial of all modules initially, ensuring broad accessibility (Table 1).

Review of Features in Other Applications

Apple Health: Apple Health serves as a foundational platform for health monitoring on the IOS operating system. However, the application primarily focuses on passive data collection. It does not aim to provide personalized experiences or influence behavior change based on the user's individual needs.

MyFitnessPal: While MyFitnessPal is strong in dietary tracking, it does not offer a personalized experience for fitness monitoring. In addition, water intake is managed as a separate module, resulting in a fragmented user experience.

Lifesum: Although Lifesum offers nutrition suggestions, these recommendations remain largely predefined for certain user segments and do not provide truly individualized dietary programs.

Fitbit: Fitbit is advanced in terms of physical measurements and sensor-based tracking; however, its recommendation features function primarily within the Fitbit device ecosystem, limiting accessibility for users who do not own compatible devices.

WaterMinder: WaterMinder focuses solely on hydration tracking. While effective for a single-purpose use case, it is limited in promoting comprehensive behavior change or providing personalized health guidance.

METHODS

Ethical approval was not required for this study as it does not involve human participants, animal subjects, or identifiable personal data. All procedures were carried out in accordance with the ethical rules and principles.

The CardioFit IOS application was developed for IOS devices using the Swift programming language and UIKit framework for user interface deisng (Akoosh et al., 2023; Serantoni et al., 2022). It integrates Firebase for backend services including user authentication via Firebase Authentication and real-time data storage and synchronization in Firebase Realtime Database for user data on dietary intake, hydration, and physical activities (Chaudhari et al., 2023; Gundavarapu et al., 2023; Wiryonoputro & Saputri, 2023). Tailored health information, exercise, and dietary plans were created with input from professional fitness coaches to deliver personalized recommendations based on user-specific parameters (Chatterjee et al., 2022; Naveed et al., 2025). The extensive use of UIKit components ensures a user-friendly and interactive interface, enhancing overall usability (Chatterjee et al., 2022).

Artificial Intelligence Model for Personalization

CardioFit IOS employs a lightweight AI-based segmentation approach not a complex deep learning architecture to personalize the user experience (Chiarito et al., 2022). The model assesses users' fundamental physical characteristics alongside their in-app behavioral patterns, clustering individuals with similar tendencies (Subramaniyaswamy et al., 2022). As a result, exercise and nutrition recommendations are dynamically shaped by the shared traits of these clusters, rather than relying solely on predefined formulas. Such personalization is essential for boosting user engagement and the effectiveness of mHealth solutions.

The model applies the K-Means unsupervised clustering algorithm, selected for its interpretability and computational efficiency, particularly in health data analysis.

Data Used

Both physical and behavioral variables were jointly evaluated for training the AI model and assigning users to appropriate clusters. The main variables used include:

- Age
- Weight
- Height
- Body-mass index (BMI)
- Basal metabolic rate (BMR)
- Physical activity level (PAL)
- Daily water consumption
- Daily recommended calorie intake

As users update their physical information or as in-app behavior changes over time, the AI mechanism reorganizes their profiles accordingly. Therefore, the model's output is not static; it continually adapts as user behavior evolves.

K-Means Unsupervised Clustering Algorithm

The K-Means algorithm, first introduced by MacQueen in 1967, has become one of the most widely used clustering methods in data mining (Ikotun et al., 2022). It aims to partition n data

Table 1. Comparison of existing application features with CardioFit

Feature	CardioFit	Apple Health	MyFitnessPal	Lifesum	Fitbit	WaterMinder
Integration of all modules on a single platform	✓	✕	✕	✕	Partial	✕
Personalized exercise planning	✓ (Karvonen + level test)	✕	✕	✕	Partial	✕
Personalized nutrition recommendations	✓	✕	Partial	✓	✕	✕
Daily water intake integration	✓	✕	✓	Partial	Partial	✓
AI-based segment analysis	✓	✕	✕	✕	✕	✕
Weekly/behavior-driven dynamic feedback	✓	✕	✕	✕	✕	✕

points into k clusters specified by the researcher, such that points within the same cluster are as similar as possible while those in different clusters are as distinct as possible (Fränti & Sieranoja, 2018). The algorithm operates through an iterative process in which cluster centers are repeatedly updated until they reach stability.

Academic and Mathematical Description of the K-Means Model

K-Means clustering is an unsupervised learning algorithm commonly used in behavioral segmentation and health data analysis due to its interpretability and low computational cost. The algorithm partitions the dataset X={x1, x2, …, xn} into kk distinct clusters by minimizing the objective function: J=∈i=1k∑xj∑Ci||xj−μi||2J=i=1∑k xj ∈Ci ∑ ||xj −μi ||2

Feature scaling was performed using StandardScaler to prevent high-range variables, such as calorie intake, from dominating the clustering process.

The optimal value of kk was determined empirically by comparing Silhouette and Davies-Bouldin scores for (k=2, 3, 4); among these, k=3 achieved the highest cluster separation (Fränti & Sieranoja, 2018).

Construction of the Synthetic Dataset

Since the application was tested by a limited number of users during the early development phase, a synthetic dataset was generated solely for proof-of-concept evaluation of the clustering mechanism. The synthetic data does not aim to represent real-world behavioral distributions and should not be interpreted as empirically validated user data.

The primary purpose of this dataset is to demonstrate the operational behavior of the proposed personalization model and to illustrate how user clusters may emerge under controlled conditions. The absence of real-world data is therefore acknowledged as a significant limitation of the current study (Vara et al. 2022, Ahmed et al. 2020).

The synthetic dataset was created by:

- Considering typical mHealth user distributions reported in the literature,
- Generating realistic values for age, BMI, PAL, water intake, and exercise duration,
- Forming a representative sample of 120 synthetic users.

This dataset was used solely to test the operational behavior of the model and to demonstrate how clusters emerge (Table 2).

Table 2. Sample records from the synthetic dataset

Age	BMI	PAL	Water (L)	Exercise (min)	Calorie	Cluster
27	21.44	1.24	1.27	26	2093	2
33	24.86	1.52	1.52	45	2458	1
42	28.42	1.79	2.15	61	2874	0
24	20.11	1.22	1.23	34	1900	2
36	25.88	1.47	1.62	49	2578	1
39	27.66	1.83	2.03	58	2983	0
23	20.54	1.22	1.11	29	1990	2
28	24.91	1.50	1.66	42	2389	1
40	27.94	1.80	2.07	63	2898	0
26	21.73	1.24	1.28	31	2008	2

BMI: Body-mass index, PAL: Physical activity level

To evaluate the clustering model during development, a synthetic dataset was generated. This approach is widely used in early-stage studies of personalized mobile health applications, as it protects patient privacy while enabling robust model testing. The dataset drew from typical mHealth user distributions in the literature to generate realistic values for age, BMI, PAL, water intake, and exercise duration, producing a representative sample of 120 synthetic users. It was used to assess the model's behavior and demonstrate cluster formation, with daily caloric requirements estimated based on BMI, PAL, and activity duration (Yun. et al., 2025).

Model Limitations

Although the clustering-based personalization mechanism provides an interpretable and computationally efficient solution, several limitations should be acknowledged.

First, the K-Means algorithm relies on Euclidean distance and assumes linear separability, which may limit its ability to capture complex and non-linear behavioral patterns. Additionally, the model remains sensitive to the predefined number of clusters (k), which may influence segmentation outcomes.

Second, the use of a fully synthetic dataset represents an idealized approximation of user behavior and does not reflect real-world variability. As a result, the findings should be interpreted as preliminary and illustrative rather than empirically validated.

Third, the current model is based on cross-sectional profile data and does not incorporate longitudinal behavioral changes over time. Temporal transitions between user clusters and their long-term impact on personalization accuracy remain an open research direction.

Future work will focus on collecting real user data, incorporating time-series analysis, and comparing K-Means with alternative clustering approaches such as Hierarchical Clustering and DBSCAN to enhance robustness and behavioral expressiveness (Ahmed et al. 2020).

Interpretation of Clusters

The model identified three distinct clusters, each guiding a tailored personalization strategy:

- **Sedentary users:** Light and progressive exercise plans.
- **Moderately active users:** Balanced and structured training plans.
- **Athletic/high-activity users:** High-intensity, performance -oriented plans (Table 3).

Evaluation of Model Performance

Clustering performance was assessed using the Silhouette Score, which quantifies cohesion within clusters relative to separation from others. The model achieved a Silhouette Score of 0.609, indicating good cluster separation (Vardakas et al., 2024). Additionally, a Davies-Bouldin Index of approximately 0.7 confirmed strong internal cluster coherence.

Impact of the Model on Application Output

User profiles from the clustering model directly shape CardioFit IOS three core modules:

Table 3. Interpretation of K-Means clustering results							
Cluster	BMI	PAL	Exercise duration	Water intake	Daily caloric requirement*	Likely user profile	Recommended goal
Cluster 1 - low activity	20-22	1.2-1.3	30 min	1.0-1.3 L	1900-2200 kcal	Young individuals with normal BMI but low activity level; sedentary workers; beginner-level users	Healthy weight maintenance or gradual weight gain; beginner exercise program
Cluster 2 - moderate activity	23-26	1.4-1.6	45 min	1.4-1.8 L	2300-2600 kcal	Users who walk regularly, have normal to slightly above-normal BMI, moderately active	Weight loss or improved conditioning; intermediate exercise program
Cluster 3 - high activity	27-30	1.7-1.9	60 min	1.9-2.4 L	2700-3200 kcal	Users with athletic background, high energy expenditure; individuals engaged in strength training	Muscle gain, performance improvement, advanced training program

*Daily caloric requirement values are estimated considering BMI, PAL, and activity duration, BMI: Body-mass index, PAL: Physical activity level

- **Exercise module:** Adapts intensity, set duration, and difficulty to the assigned cluster.
- **Diet module:** Personalizes daily calorie targets and meal suggestions by cluster.
- **Water intake module:** Dynamically adjusts reminder frequency and hydration targets based on the profile.

This integration delivers personalized, adaptive recommendations that evolve beyond static lists to behavior- and profile-driven guidance.

Application Modules and Structure

Addressing the fragmentation common in existing mobile health tracking applications which often focus on isolated aspects CardioFit IOS offers a comprehensive, integrated solution. The app is structured around three core modules that enable seamless management of daily health activities within a single platform.

Exercise Tracking Module

The exercise tracking module, a central feature of CardioFit IOS, delivers a personalized program based on onboarding information and user objectives. It monitors key physical activities to help users achieve their health and fitness goals.

Upon entering the exercise section, users select from two main categories: cardio and fitness. Each offers programs at three difficulty levels beginner (4-week plans), intermediate (8-week), and advanced (12-week) with one to three options per level, all developed with input from professional fitness coaches (Iolascon et al., 2021).

Users choose a level based on self-assessment; for those unsure, the International Physical Activity Questionnaire determines a suitable starting point for tailored progression.

Cardio Module Details

The cardio module tracks activities like running, swimming, brisk walking, and cycling, recording and analyzing data such as heart rate and calories burned. Prior to use, the user's target heart rate is calculated via the Karvonen formula using age and resting heart rate (Karvonen & Vuorimaa, 1988; Olsson et al., 2022). Although widely used for prescribing exercise intensity, this predictive method requires caution due to individual physiological variations.

This approach defines intensities for beginner, intermediate, and advanced plans, with gradual increases as users progress. Such progression enhances aerobic capacity and cardiovascular health safely, optimizing adaptation while minimizing overexertion and injury risks (Milani et al., 2024).

Exercise Intensity Percentages

Exercise intensity is categorized by exertion level, aligning with physiological goals that influence metabolic, hormonal, and cardiorespiratory responses:

- **Low intensity:** Ideal for activity novices, this builds basic movement skills and eases adaptation to exercise (Taylor et al., 2021).
- **Weight control:** Moderately intense to maximize fat burning, boosting energy expenditure for weight management and fat reduction (MacIntosh et al., 2021).
- **Aerobic:** Strengthens the cardiovascular system and enhances fat utilization, improving heart-lung capacity and endurance (Koman et al., 2024).
- **Anaerobic:** High-intensity for building muscle strength and performance, demanding near-maximal effort (Patel et al., 2017).

These categories guide program customization to users' goals and fitness levels.

Exercise Duration Protocols

CardioFit IOS includes structured protocols for 8-week and 12-week exercise programs that progressively increase in frequency, duration, and intensity to optimize adaptation and minimize injury (Rospo et al., 2016) (**Table 4, 5**).

Sex-Specific Basal Metabolic Rate Calculations: a Rationale for Differentiation

The differentiation in basal metabolic rate calculations between males and females is not an inconsistency but a critical aspect for maintaining accuracy, predicated on fundamental physiological distinctions between the sexes. The utilization

Table 4. Exercise duration protocol for an 8-week program						
Weeks	Sessions per week	Warm-up (min)	Stretching (min)	Exercise intensity	Target energy expenditure (kcal)	Session duration (min)
1-2	2	10	5	50% HRMax	150	20
3-4	2	10	5	50% HRMax	200	30
5-6	3	10	5	60% HRMax	250	35
7-8	3	10	5	60% HRMax	300	35

Table 5. Exercise duration protocol for a 12-week program

Weeks	Sessions per week	Warm-up (min)	Stretching (min)	Exercise intensity	Target energy expenditure (kcal)	Session duration (min)
1-2	2	10	5	50% HRMax	200	30
3-4	3	10	5	60% HRMax	200	30
5-8	4	10	5	70% HRMax	300	40
9-12	4	10	5	70% HRMax	400	50

of sex-specific predictive equations, such as the Mifflin-St. Jeor equation, ensures that applications like CardioFit IOS provide metabolically consistent and scientifically grounded estimations of energy expenditure.

Physiological basis for sex-specific BMR calculations: Variations in BMR between sexes are primarily driven by differences in body composition, hormonal profiles, and average body dimensions:

- **Body composition:** Males typically exhibit a higher proportion of lean body mass, particularly skeletal muscle tissue, compared to females. Given that muscle tissue is metabolically more active than adipose tissue, a greater LBM contributes to a higher absolute BMR in males (Jagim et al., 2023). Conversely, females generally possess a higher percentage of body fat, which is metabolically less active, thereby contributing to a comparatively lower BMR even when adjusted for overall body mass (Ferraro et al., 1992).
- **Hormonal influences:** Sex hormones significantly modulate energy metabolism and body composition. Testosterone in males promotes muscle anabolism, while estrogen in females influences fat distribution and has been observed to impact resting energy expenditure, with studies showing that estrogen administration can increase resting energy expenditure (Weidlinger et al., 2023). These distinct hormonal landscapes contribute to differing metabolic profiles, influencing overall energy homeostasis and metabolism between men and women (Mauvais-Jarvis, 2015, 2023; Sanchez et al., 2024).
- **Anthropometric averages:** On average, males tend to be taller and possess greater body mass than females. While height and weight are direct inputs into BMR predictive equations, the cumulative effect of these anthropometric differences also contributes to the observed variations in BMR between sexes.

Consistency in the Mifflin-St. Jeor equation: The Mifflin-St. Jeor equation systematically accounts for these physiological sex differences through distinct constant terms within its formulation. The development of this predictive equation involved multiple-regression analyses derived from data on a substantial cohort of healthy subjects, leading to empirically established relationships between resting energy expenditure and factors such as weight, height, and age (Mifflin et al., 1990). The equations are as follows:

- **Female BMR:** BMR = [9.99 x weight (kg)] + [6.25 x height (cm)] – [4.92 x age (years)] - 161
- **Male BMR:** BMR = [9.99 x weight (kg)] + [6.25 x height (cm)] – [4.92 x age (years)] + 5

The distinct constant values (-161 for females and +5 for males) are empirically derived adjustments. These constants were specifically determined through statistical analysis to optimize the fit between predicted and measured BMRs for each sex, reflecting the integrated effects of body composition, hormonal regulation, and average anthropometrics (Mifflin et al., 1990). Therefore, these sex-specific calculations do not represent an inconsistency; rather, they constitute an academically rigorous and physiologically accurate methodology for estimating BMR, making them entirely appropriate and necessary for precise application within platforms like CardioFit IOS.

Physical Activity Level Multipliers

The physical activity level multipliers are essential for calculating total energy expenditure by adjusting the BMR based on an individual's activity level (**Table 6**).

Table 6. Physical activity levels

Physical activity level	Multiplier
Sedentary	1.0-1.39
Lightly active (light exercise or sports, 1-3 days per week)	1.4-1.59
Moderately active (moderate exercise or sports, 3-5 days per week)	1.6-1.89
Very active (intense exercise or sports, 6-7 days per week)	1.9-2.5

Calculation of Total Energy Expenditure

Once the total energy expenditure is calculated, the application determines the user's daily caloric needs and provides tailored guidance (Bianchetti et al., 2022). This approach helps users maintain energy balance and achieve their specific health goals. It then presents a variety of meal options, including both user-created and recommended meals customized to their preferences. These suggestions account for factors such as physical activity, meal history, height, and weight (Papastratis et al., 2024). The module integrates open-source APIs to compile comprehensive meal lists with nutritional values, images, and total caloric content (Han & Chen, 2024). Daily meal data is recorded in a Firebase database, allowing users to track progress over time and visualize dietary performance through graphs.

Hydration Tracking Module

The CardioFit IOS application enables users to log their daily water consumption alongside dietary intake. Similar to dietary tracking, users can customize their daily target water intake to match personal preferences (Cruz et al., 2021; Pauley et al., 2024). By default, the app calculates an individual's daily water requirement using a standardized formula based primarily on body weight, offering personalized guidance though more advanced models incorporate additional intrinsic and extrinsic factors, such as activity level or climate (Dolci et al., 2022). This formula is shown below. Meanwhile, wearable technologies and smart devices are emerging as complementary tools for monitoring fluid intake.

Daily Water Requirement Equation

Daily water requirement = body weight x 35 ml

Users can view their daily water consumption in real-time through graphical visualizations powered by data stored daily in a Firebase database. This setup helps them track progress, manage hydration habits, and access detailed analyses to achieve long-term goals (Reeves et al., 2023).

DISCUSSION

The CardioFit IOS application addresses a critical need within the mobile health (mHealth) landscape by offering a comprehensive, integrated platform for exercise, diet, and hydration tracking. Existing literature highlights the prevalent issue of fragmentation in mHealth applications, where users often resort to multiple single-purpose apps, leading to disjointed experiences and diminished long-term adherence (Tomlinson et al., 2013). CardioFit IOS directly counters this by consolidating these essential health management functions into a single ecosystem, fostering a more streamlined and efficient user journey, an approach supported by research advocating for integrated solutions in chronic disease management (Ferreira et al., 2024).

A core strength of CardioFit IOS lies in its personalized approach, driven by an artificial intelligence mechanism utilizing K-Means unsupervised clustering. This contrasts with many existing applications that offer predefined or limited personalization, often failing to adapt to the dynamic and evolving needs of users (Zhu et al., 2021). While personalization is recognized as essential for enhancing user engagement and effectiveness in mHealth (Rivera-Romero et al., 2023), CardioFit IOS's strategy of clustering users based on both physical characteristics and in-app behavioral patterns allows for the dynamic shaping of recommendations, aiming to mitigate the "personalization paradox" the inherent conflict between user modeling and adaptation in behavior change applications (Zhu et al., 2021). The use of K-Means for user segmentation is a recognized technique in customer segmentation and behavior analysis, valued for its interpretability and computational efficiency (Salminen et al., 2023).

The application's detailed exercise module incorporates the Karvonen formula for heart rate-based intensity prescription (Hofmann & Tschakert, 2017) and structured duration protocols, providing a scientifically grounded framework for physical activity (Arora et al., 2023). Similarly, the diet and hydration modules offer personalized targets and recommendations, utilizing established equations for basal metabolic rate and total energy expenditure calculations (Prado-Nóvoa et al., 2024), further enhancing the individualized nature of the application (Abeltino et al., 2024).

Despite its advantages, the current implementation of CardioFit IOS acknowledges several limitations, consistent with broader challenges in mHealth AI. The reliance on K-Means clustering, while interpretable, may struggle to capture complex, non-linear behavioral patterns due to its dependence on Euclidean distance, and its performance can be sensitive to noise and the need to specify the number of clusters a priori (Zahra et al., 2015; Zhang et al., 2025). Furthermore, the initial development and evaluation were conducted using a synthetic dataset (Giuffré & Shung, 2023). While useful in early-stage studies for protecting privacy and evaluating model behavior, such data represent idealized user distributions rather than real-world variability (Breugel et al., 2023). This highlights a general challenge in mHealth app research, where practical implementation faces hurdles related to efficacy, uptake, usability, and patient outcomes (Birkhoff & Moriarty, 2020).

Future work will focus on collecting real-world user data, exploring alternative clustering algorithms, and developing a hybrid model that integrates supervised learning techniques (Rauba et al., 2024).

Limitations

The clustering-based personalization mechanism, while offering a lightweight and interpretable solution, presents inherent limitations. First, K-Means relies on Euclidean distance and may fail to capture non-linear behavioral patterns. Second, the synthetic dataset represents idealized user distributions rather than real-world variability, potentially leading to performance gaps when transitioning to authentic scenar IOS. Third, the current personalization engine depends primarily on profile-level data and does not yet incorporate longitudinal changes in user behavior.

CONCLUSION

This study identified limitations in existing mobile health applications that fragment the user experience, prompting the development of CardioFit IOS. The application provides a personalized, holistic solution for tracking health, diet, and exercise, empowering users to adopt sustainable healthy lifestyle habits. CardioFit IOS introduces key innovations, including integrated monitoring of exercise, diet, and hydration in a single platform. This directly addresses the challenge of juggling multiple apps, while its user-friendly interface enhances accessibility and practicality for daily health management. At the core of the app's effectiveness is its AI mechanism, which uses a lightweight K-Means unsupervised clustering algorithm for dynamic user segmentation. Rather than relying on static recommendations, it analyzes users' physical characteristics and in-app behaviors, grouping those with similar patterns into evolving clusters. As a result, exercise intensities, diet targets, and hydration reminders adapt continuously to each user's profile and cluster traits, delivering truly personalized health plans. In conclusion, CardioFit IOS advances mHealth through its integrated platform and intelligent personalization. By leveraging AI for dynamic, profile-driven recommendations alongside comprehensive tracking, it empowers users to achieve their health and wellness goals. Ongoing refinements based on user feedback and addressing the identified limitations will further enhance this innovative tool.

ETHICAL DECLARATIONS

Ethics Committee Approval

Ethical approval was not required for this study as it does not involve human participants, animal subjects, or identifiable personal data.

Peer Review Process

This manuscript was subject to external peer review.

Conflict of Interest

The authors declare no conflicts of interest related to this study.

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Author Contributions

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