

IoT-Based Elderly Exercise Guidance and Versatile Positioning Tracking System [†]

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Abstract

With the rapid growth of the aging population, decreased muscle strength, reduced physical activity, and increased risk of cognitive decline have become significant challenges in elderly care. To solve these problems, we developed an IoT-based versatile positioning tracking system for elderly exercise. The system integrates wearable sensing devices, motion recognition, indoor and outdoor positioning technologies, and cloud-based data analysis to provide personalized exercise guidance and real-time safety monitoring for the elderly. By collecting information on the height, weight, age, and gender of the elderly, the system calculates the basal metabolic rate and total daily energy expenditure to generate individualized calorie surplus and muscle-strengthening exercise plans. The health exercise subsystem combines a triaxial accelerometer and camera-based motion recognition to evaluate exercise correctness and calculate real-time energy consumption. In addition, the positioning subsystem utilizes wireless fidelity signal strength for indoor localization and the global positioning system for outdoor positioning to continuously monitor the elderly's location. When the elderly leave the predefined safe area or enter a dangerous zone, the notification subsystem immediately sends alerts to caregivers using Discord and provides voice reminders using Google Text-to-Speech. The web-based query subsystem is developed to enable caregivers to review historical exercise records, location data, and event logs within specific time ranges. By integrating exercise guide, safety monitoring, and caregiver notification into a unified system, muscle endurance is enhanced, health risks are reduced, and the quality of life for the elderly is enhanced. The developed system achieves the United Nations Sustainable Development Goals, particularly “Goal 3: Good Health and Well-being” and “Goal 11: Sustainable Cities and Communities”.

Keywords: elderly care; IoT; exercise guide; indoor positioning; location tracking; health monitoring



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1. Introduction

A rapidly aging population makes elderly health increasingly important. Aging is accompanied by declining muscle strength, reduced physical activity, and cognitive deterioration, which increase the risks of falls and wandering incidents. Therefore, promoting safe exercise while ensuring daily safety monitoring has become a critical challenge in elderly care.

Regular physical exercise improves muscle endurance and maintains physical function in older adults. However, many elderly people are unable to exercise independently due to insufficient muscle strength, incorrect postures, or the lack of real-time guidance. In addition, most existing fitness and health monitoring systems are designed for the young and fail to address the physiological characteristics and safety needs of older adults. To address these issues, we developed an IoT-based elderly exercise guidance and versatile positioning tracking system.

The system records personal information, including height, weight, age, and gender, and applies basal metabolic rate (BMR) and total daily energy expenditure (TDEE) models to generate personalized exercise and calorie management plans suitable for the elderly. The health exercise subsystem developed integrates wearable three-axis accelerometers with camera-based motion recognition to monitor exercise movements and evaluate posture correctness in real time. The localization subsystem tracks the elderly position using wireless fidelity (Wi-Fi) based indoor positioning and the global positioning system (GPS) based outdoor localization technologies. When predefined conditions are triggered, such as leaving a safe zone or entering a dangerous area, the notification subsystem sends alerts to caregivers. In addition, a web-based query subsystem allows caregivers to review historical exercise and location records. By integrating exercise guidance, location tracking, and caregiver notification into a unified platform, the developed system aims to improve muscle endurance, reduce safety risks, and enhance daily care efficiency for the elderly. Furthermore, this study contributes to the United Nations Sustainable Development Goals, particularly “Goal 3: Good Health and Well-Being” and “Goal 11: Sustainable Cities and Communities”.

The remainder of this paper is organized as follows. Section 2 reviews related research and technologies, Section 3 presents the system architecture, Section 4 describes system implementation, and Section 5 concludes the paper.

2. Related Technology

National Tsing Hua University in Taiwan proposed an image recognition approach to analyze joint angles during rope skipping exercises using a single-camera setup [1]. The system performed two-dimensional (2D) motion detection to estimate joint movements. However, due to the limitation of a single viewing angle, the accuracy of depth perception and rotational angle estimation remained insufficient. In contrast, the developed system in this study integrates wearable three-axis accelerometers to directly detect joint movement correctness and provides real-time voice feedback when incorrect postures are detected, assisting the elderly in immediately correcting their movements during exercise.

National Taiwan University in Taiwan developed a passive indoor localization system using a received signal strength indicator (RSSI) fingerprinting through Wi-Fi sniffers operating in monitor mode [2]. The system showed relatively high positioning accuracy by collecting extensive signal strength data and constructing fingerprint databases in advance. However, this approach required significant pre-deployment data collection and resulted in high implementation costs, whereas the system mainly focused on localization accuracy without considering safety-related applications. In contrast, RSSI-based trilateration is adopted in the developed system as the core positioning method and integrates safe zone detection, voice alerts, and real-time notifications, enabling caregivers to promptly monitor and respond to abnormal location events of older adults.

National Central University in Taiwan researched a wearable fall detection system for construction site environments using accelerometer-based motion analysis [3]. The system demonstrated high detection accuracy under controlled conditions. Nevertheless, sensors mounted on the head or feet were prone to misclassifying daily activities as fall

events, leading to false alarms. In contrast, the developed system combines camera-based motion verification with wearable three-axis accelerometers attached to the waist and knee, improving motion recognition accuracy and reducing misclassification through multi-sensor validation.

Takming University of Science and Technology in Taiwan proposed a smart, customizable spinning system designed specifically for stationary cycling exercises [4]. The system provided personalized fitness recommendations based on user information and monitored exercise performance using integrated sensors. However, the application of the system was limited to spinning equipment, making it inappropriate for users engaging in other types of exercises. In contrast, the developed system provides general elderly exercise guidance by considering personal parameters such as height, weight, age, and gender, as well as recommended daily energy expenditure. The system also suggests personalized muscle-strengthening exercise through voice-guided exercise control and integrates location tracking and caregiver notifications to enhance overall safety and usability.

3. System Architecture

The developed system integrates health exercise, localization, central computing, notification, and query subsystems into a unified architecture designed to monitor physical activity, track the location, and support caregiver interventions. Each subsystem interacts through the Firebase cloud database, which serves as the central repository for user data, exercise records, and localization results.

Figure 1 shows the overall architecture and data flow. At its core, the central computing subsystem coordinates user registration, login sessions, exercise monitoring, and location analysis. It manages database updates and triggers notifications when predefined conditions are met. The health exercise subsystem collects motion data and verifies posture, while the localization subsystem determines user position using Wi-Fi RSSI indoors and GPS outdoors. The notification subsystem delivers alerts to caregivers and users, and the query subsystem provides caregivers with access to historical records and visualizations. The health exercise subsystem performs pose verification and motion tracking. Finally, the localization subsystem conducts location tracking using Wi-Fi and GPS.

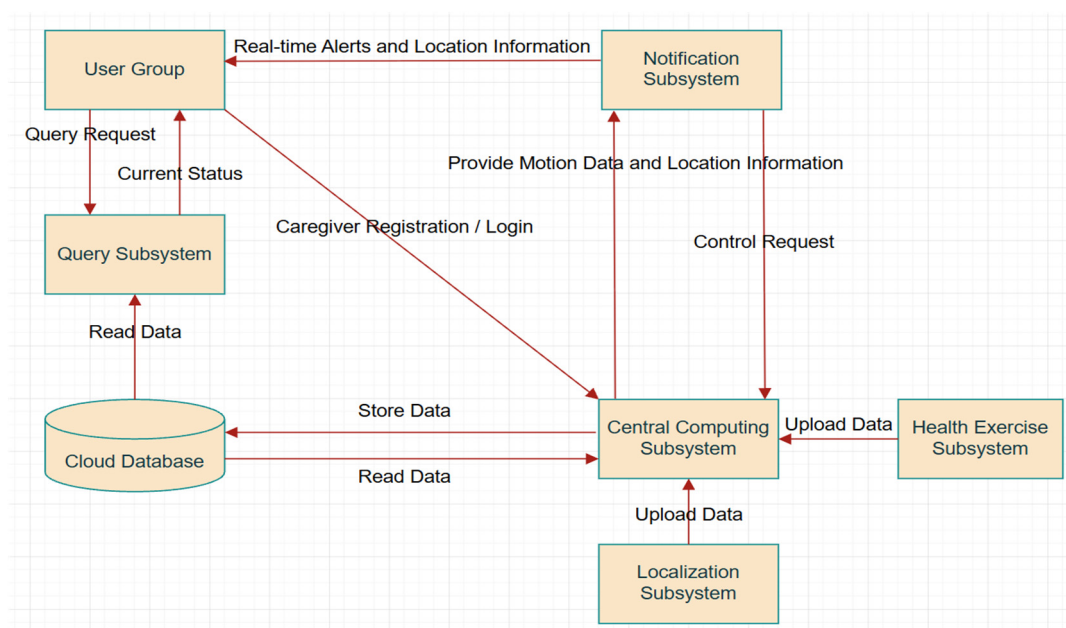


Figure 1. System architecture and data flow.

3.1. Health Exercise Subsystem Architecture

This subsystem uses accelerometer and camera-based motion capture data. It evaluates exercise movements, posture correctness, and energy consumption. Results are transmitted to the central computing subsystem and stored in the database at 10 min intervals (Figure 2).

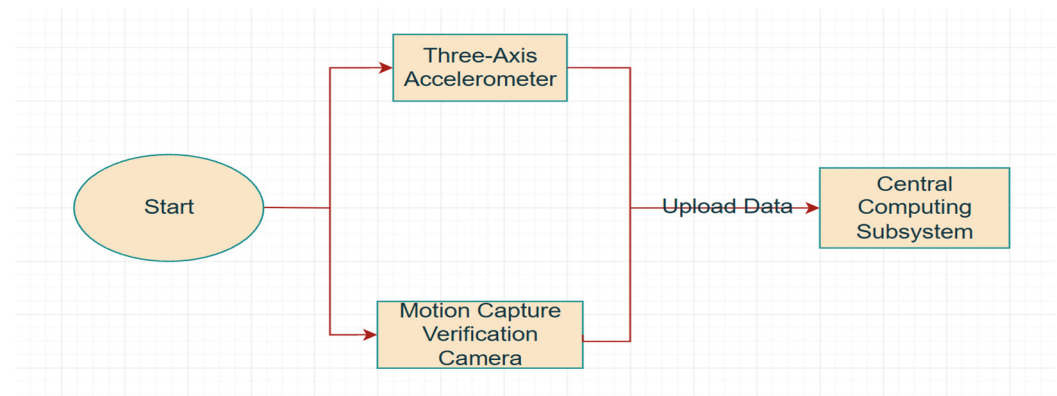


Figure 2. The operation flow of the health exercise subsystem.

3.2. Localization Subsystem Architecture

Indoor localization is performed using Wi-Fi trilateration at 20 s intervals. If the user remains outside the safe zone for six consecutive detections, a notification is triggered and data are synchronized to the database. When fewer than three Wi-Fi access points are detected, GPS-based localization is activated, updating location every two minutes (Figure 3).

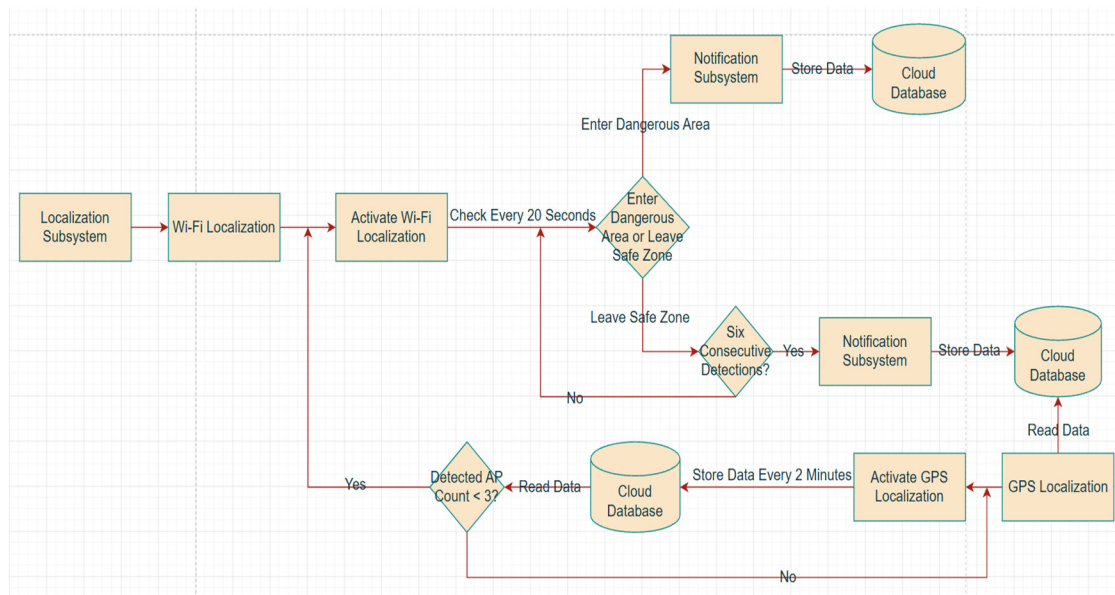


Figure 3. The operation flow of the localization subsystem.

3.3. Central Computing Subsystem Architecture

This subsystem distinguishes between registration and login events. Upon login, personal data are retrieved and stored. During exercise sessions, camera detection initiates monitoring, and exercise data are stored periodically. If no user is detected, localization is activated. The subsystem also evaluates exercise goal completion and triggers notifications when goals are achieved (Figure 4).

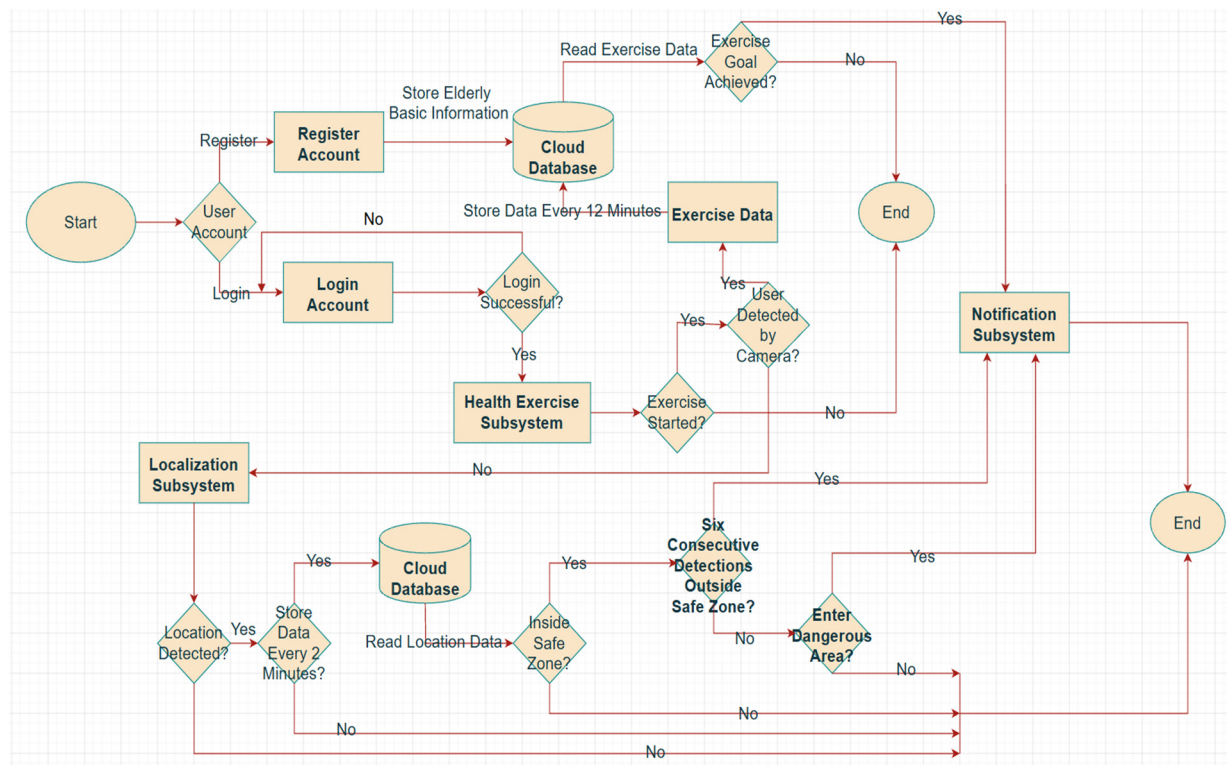


Figure 4. The operation flow of the central computing subsystem.

3.4. Notification Subsystem Architecture

The subsystem retrieves calorie targets and accumulated consumption data, as well as localization results, from the database. Alerts are dispatched when the user enters hazardous areas, leaves safe zones, or achieves exercise goals, using Google Text-to-Speech (Google Cloud Text-to-Speech API, Google LLC, Mountain View, CA, USA; <https://cloud.google.com/text-to-speech>, accessed on 20 May 2026) and Discord (Figure 5).

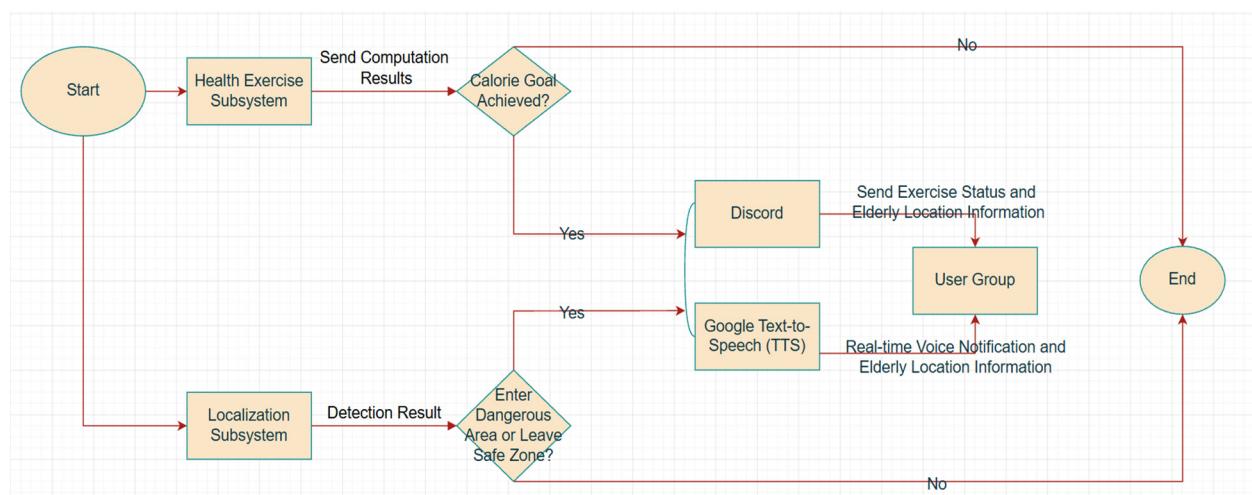


Figure 5. The operation flow of the notification subsystem.

3.5. Query Subsystem Architecture

Caregivers query historical records, including energy consumption, BMR, TDEE, and daily expenditure. Graphical visualizations display exercise outcomes and safe zone transitions (Figure 6).

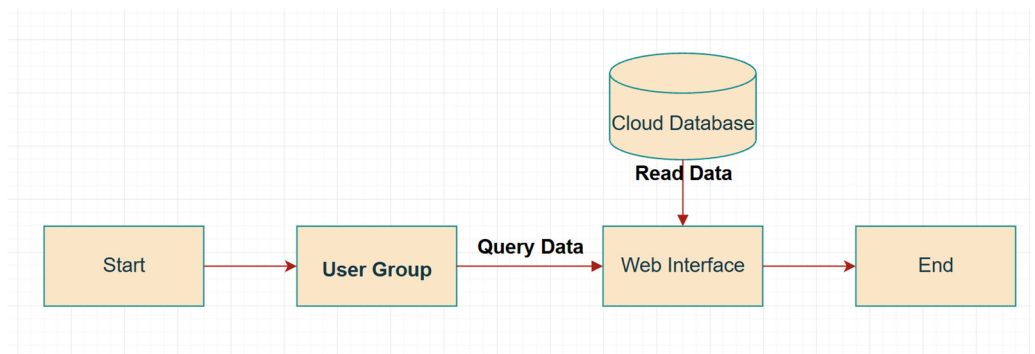


Figure 6. The operation flow of the query subsystem.

4. System Implementation

4.1. Caregiver Registration and Login Interface

To ensure data security and identity verification, caregivers must first register an account. During registration, the caregiver provides an email address, and the system automatically sends a random verification code to that inbox. Entering the correct code activates the account. After registration, caregivers can access the system by logging in with their registered email and password, as illustrated in Figures 7 and 8.

The figure shows two screenshots of the caregiver registration and verification interface. The left screenshot displays the 'Registration' form with fields for 'Name' (Full Name), 'Account' (Set Username), and 'Password' (Set Password). It includes a 'Sign Up' button and a 'Back' button. A language selection button 'EN / CN' is visible. The right screenshot shows the verification screen with the message 'Registration successful! Please login.' and an 'OK' button. It also displays a '4-Digit Code' (3491) and a 'Confirm' button. A debug message '(Debug: 3491)' is visible.

Figure 7. Caregiver registration and verification (the UI button “EN/CN” indicates language selection).

The figure shows the 'Login' interface. It features a language selection button 'EN / CN' and a title 'Login'. Below the title, there are two input fields: 'Account' (containing 'Tom') and 'Password' (containing '....'). At the bottom, there are two buttons: 'Login' (blue) and 'Register' (grey).

Figure 8. Caregiver login interface (the UI button “EN/CN” indicates language selection).

4.2. Elder Adult Basic Information Registration

After a caregiver logs in, the caregiver manages the basic personal information of the elder adult. The input data include gender, date of birth, height, weight, and other physiological parameters (Figure 9). Based on the input information, the system calculates the BMR [5] (Table 1) and TDEE [5] (Table 2). The corresponding physical activity level values and field descriptions used for these calculations are provided as shown in Table 3, enabling related health indicators to be established for personalized exercise planning.

Figure 9. Elder adult basic personal information input.

Table 1. BMR calculation formula.

Gender	BMR	Example Profile and Results
Male	$(13.7 \times \text{Weight (kg)}) + (5.0 \times \text{Height (cm)}) - (6.8 \times \text{Age}) + 66$	175 cm, 76 kg, 63 years old ≥ 1553.8 kcal
Female	$(9.6 \times \text{Weight (kg)}) + (1.8 \times \text{Height (cm)}) - (4.7 \times \text{Age}) + 655$	162 cm, 57 kg, 65 years old ≥ 1188.3 kcal

Table 2. TDEE calculation formula.

Gender	TDEE (BMR $\times$ Activity Level)
Male	TDEE = $1553.8 \times 1.375 = 2136.48$ kcal
Female	TDEE = $1188.3 \times 1.375 = 1633.91$ kcal

Table 3. Physical activity levels for exercise categories.

Exercise	Description	Activity Level
Light activity	Exercise 1–3 days per week	1.375
Moderate activity	Exercise 3–5 days per week	1.55
High activity	Exercise 6–7 days per week	1.725

The metabolic equivalent of task (MET) is used to quantify the energy expenditure required for human physical activities. During physical activity, energy is generated through carbohydrate and fat oxidation, accompanied by oxygen consumption. Therefore, oxygen consumption can be used as an indicator of exercise intensity, where higher oxygen consumption corresponds to greater exercise intensity. To calculate exercise energy expenditure [6], one MET is defined as an energy consumption rate of 1 kcal per kilogram of body weight per hour (1 MET = 1 kcal/kg·hour). The total calories burned during exercise are calculated using Equation 1. Different MET values are assigned to resting, low-intensity, moderate-intensity, and high-intensity activities. The selected MET values for exercise and rest conditions are presented in Table 4 [7–9].

$$\text{Exercise energy consumption (kcal)} = \text{MET} \times \text{body weight (kg)} \times \text{exercise duration (hour)} \quad (1)$$

Table 4. MET for rest and different exercise intensities.

Exercise Intensity	MET
Rest	1 MET (assigned as 1.0 MET)
Low intensity	1.6–2.9 MET (assigned as 2.5 MET)
Moderate intensity	3.0–5.9 MET (assigned as 4.5 MET)
High intensity	≥6 MET (assigned as 6.0 MET)

The estimated daily energy expenditure and exercise calories for different older adults are shown in Table 5. The results include energy consumption for one exercise set, as well as accumulated values for 12 min and 36 min exercise durations.

Table 5. Daily energy expenditure and exercise calories of elder adults.

Elder Adult Profile	TDEE (kcal)	Energy per Set (kcal)	12 min Exercise (kcal)	36 min Exercise (kcal)
Example 1	2136.48	5.70	22.80	68.40
Example 2	1633.91	4.28	17.12	51.36

After the age of 30, skeletal muscle mass declines at a rate exceeding 1% per year when resistance training and adequate nutrition are lacking, resulting in reduced metabolic rate and diminished physical performance in older adults [10]. Muscle growth requires a caloric surplus, defined as daily energy intake exceeding the individual's TDEE. This surplus provides the energy necessary for muscle protein synthesis and recovery. In the absence of a caloric surplus, sustained muscle accumulation is unlikely [10]. The calculation of caloric surplus for muscle gain is presented in Equation (2).

$$\text{Caloric surplus (muscle gain)} = \text{daily caloric intake} - \text{TDEE} \quad (2)$$

The recommended daily caloric intake table is applied to older adults with normal body weight when muscle gain is selected as the exercise goal [11] (Figure 10).

Daily activity level	Calorie requirements for underweight individuals	Calorie requirements for people of normal weight	Calorie requirements for overweight or obese individuals
Light work	35 kcal × current weight (kg)	30 kcal × current weight (kg)	20–25 kcal × current weight (kg)
Moderate work	40 kcal × current weight (kg)	35 kcal × current weight (kg)	30 kcal × current weight (kg)
Heavy work	45 kcal × current weight (kg)	40 kcal × current weight (kg)	35 kcal × current weight (kg)

Figure 10. Daily activity scale.

The system calculates the older adult's TDEE based on gender, age, height, and weight, and then estimates the muscle gain target using two representative cases (Examples 1 and 2 in Table 1). The schematic is shown in Figure 11.

Parameter	Example 1 (Ann)	Example 2 (Nmm)
Name	Ann	Nmm
Gender	Male	Female
Age	63 years old	65 years old
Height (cm)	175 cm	162 cm
Weight (kg)	76 kg	57 kg
Intensity Table	Light (30)	Light (30)
Calculate		
BMR	1553.8 kcal	1188.30 kcal
TDEE	2136.5 kcal	1633.91 kcal
Muscle Goal	143.5 kcal	76.09 kcal

Figure 11. Calculated BMR, TDEE, and health indicators.

4.3. Health Exercise Subsystem

This subsystem system features an integrated interface for real-time exercise tracking and motion analysis. Upon activation, it executes iterative energy expenditure calculations for each 12 min training cycle as shown in Figure 12. A camera-based module classifies user movements into standing, correct, or incorrect states. To facilitate precise posture correction, the interface provides intuitive feedback by dynamically overlaying bounding boxes on the video stream to indicate detected body regions and sensor positions as shown in Figure 13.

Panel	Timer	Total Calories	Rules
Left	09:00	0.00 kcal	• Cycle: 1m Exercise, 2m Rest • Total: 12m, Auto-save enabled • Reset: After 2 cumulative errors
Right	12:00	0.00 kcal	• Cycle: 1m Exercise, 2m Rest • Total: 12m, Auto-save enabled • Reset: After 2 cumulative errors

Figure 12. Initial exercise interface before pressing “Start Training”.

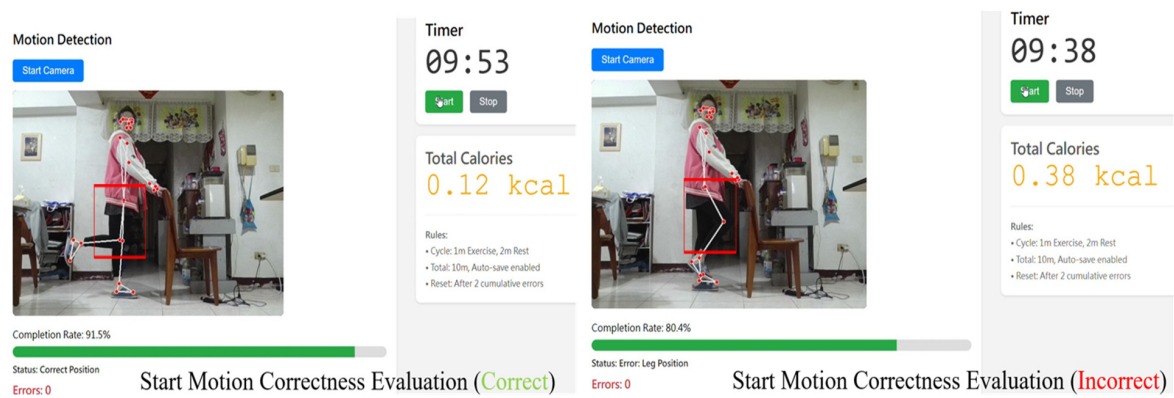


Figure 13. Real-time posture classification and visual feedback for correct and incorrect movements.

The health exercise subsystem employs wearable three-axis accelerometer modules attached to the waist and knee of the older adult. These sensors continuously collect acceleration data along three axes during exercise. The collected signals are transmitted to the central processing unit using ESP32 microcontroller (Espressif Systems, Shanghai, China) for real-time motion analysis. This wearable sensing design enables continuous monitoring of lower-limb movement patterns during rehabilitation and daily exercise activities as shown in Figure 14.



Figure 14. Sensors attached to the waist and knee for real-time motion data acquisition.

To enhance motion assessment accuracy, the subsystem fuses three-axis accelerometer data with camera-based posture recognition results as shown in Figure 15. The system generates two-dimensional motion trajectories to visualize the movement paths of the waist and knee as shown in Figure 16. This multimodal fusion allows caregivers to observe motion stability, balance, and movement consistency. The trajectory visualization supports detailed evaluation of exercise quality as shown in Figures 17 and 18.

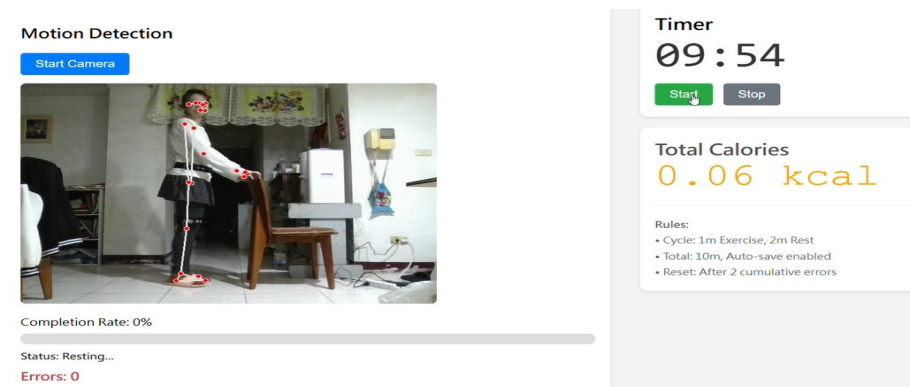


Figure 15. Monitoring interface for the wearable 3-axis accelerometer.

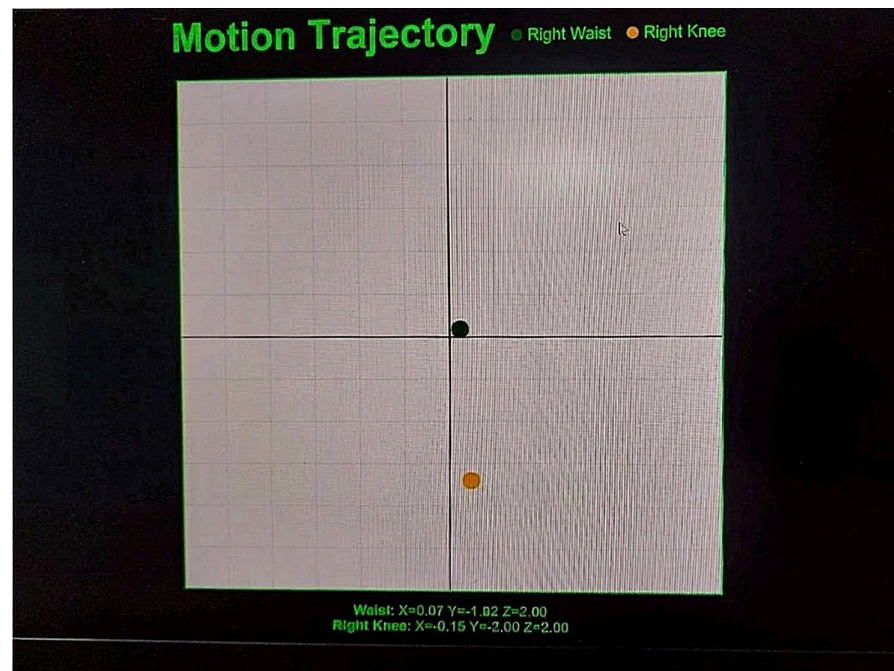


Figure 16. Motion trajectory visualization.

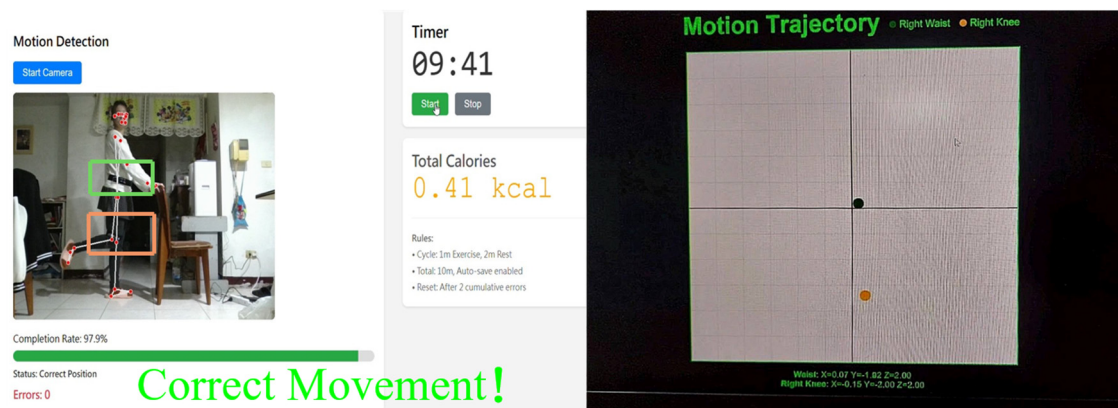


Figure 17. Correct movement (the green and orange frames indicate the tracked body joint regions).



Figure 18. Incorrect movement (the green and orange frames indicate the tracked body joint regions).

4.4. Localization Subsystem

The indoor localization subsystem estimates the position of the older adult based on Wi-Fi signal strength from nearby access points as shown in Figures 19 and 20. The subsystem defines a safe zone and one or more predefined dangerous areas. When the older adult enters a restricted or dangerous area, the system immediately detects the event and triggers the corresponding safety mechanisms as shown in Figure 21.

```
[Firestore] Connected
[Startup] Scanning environment Wi-Fi ...

[Nearby AP List (SSID -> RSSI)]
SSID=TP-Link_184          RSSI=-46 dBm  BSSID=1c:3b:f3:ef:21:50:
SSID=TP-Link_184_5G      RSSI=-48 dBm  BSSID=1c:3b:f3:ef:21:4f:
SSID=kbro186-2.4G        RSSI=-90 dBm  BSSID=68:02:b8:d2:61:c7:
SSID=Hidden Network      RSSI=-91 dBm  BSSID=6e:02:b8:d2:61:c7:
SSID=ASUS_30             RSSI=-95 dBm  BSSID=50:eb:f6:0c:fa:30:
SSID=HITRON-D560-5G      RSSI=-95 dBm  BSSID=be:3e:07:66:d5:60:
SSID=[LG_Wall-Mount A/C]b48c RSSI=-100 dBm BSSID=ba:16:5f:f9:b4:8c:
```

Figure 19. Real-time scanning and RSSI acquisition of ambient Wi-Fi signals.

```
Please enter [Home Network Name (case-sensitive)]: TP-Link_184

[Selected Access Points for Trilateration]
-> AP1 (Home): TP-Link_184      | BSSID: 1c:3b:f3:ef:21:50: | RSSI: -46 dBm
-> AP2      : TP-Link_184_5G    | BSSID: 1c:3b:f3:ef:21:4f: | RSSI: -43 dBm
-> AP3      : ASUS_30           | BSSID: 50:eb:f6:0c:fa:30: | RSSI: -96 dBm
```

Figure 20. Selection of optimal reference nodes based on peak signal strength for trilateration.

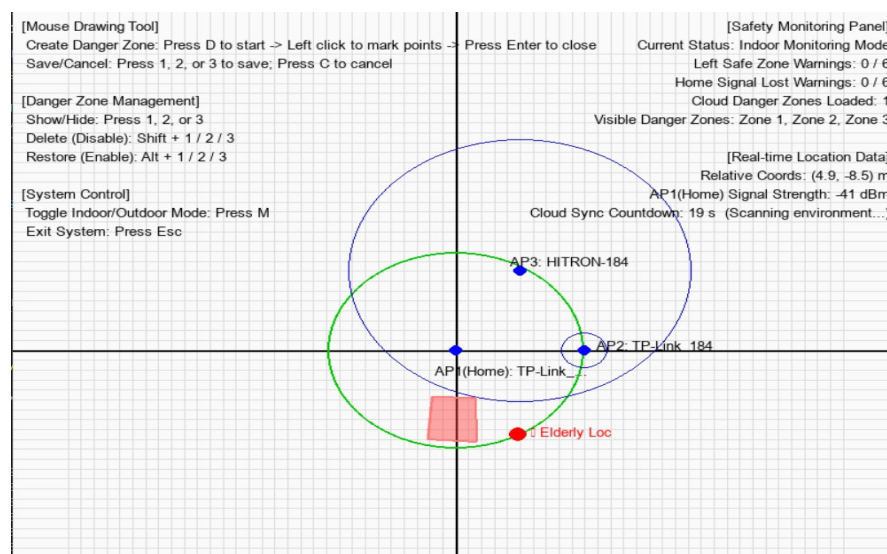


Figure 21. Indoor localization and dangerous area detection: Wi-Fi access point coverage (blue circle), safe zone (green circle), dangerous area (red rectangle), and current location of the older adult (red dot).

When the number of detected Wi-Fi access points is fewer than three as shown in Figure 22. The system switches from indoor localization mode to outdoor GPS-based localization mode. In outdoor mode, the older adult's location is visualized using Google Maps (Google Maps Platform JavaScript API, v3) to provide caregivers with real-time geographic information as shown in Figure 23.

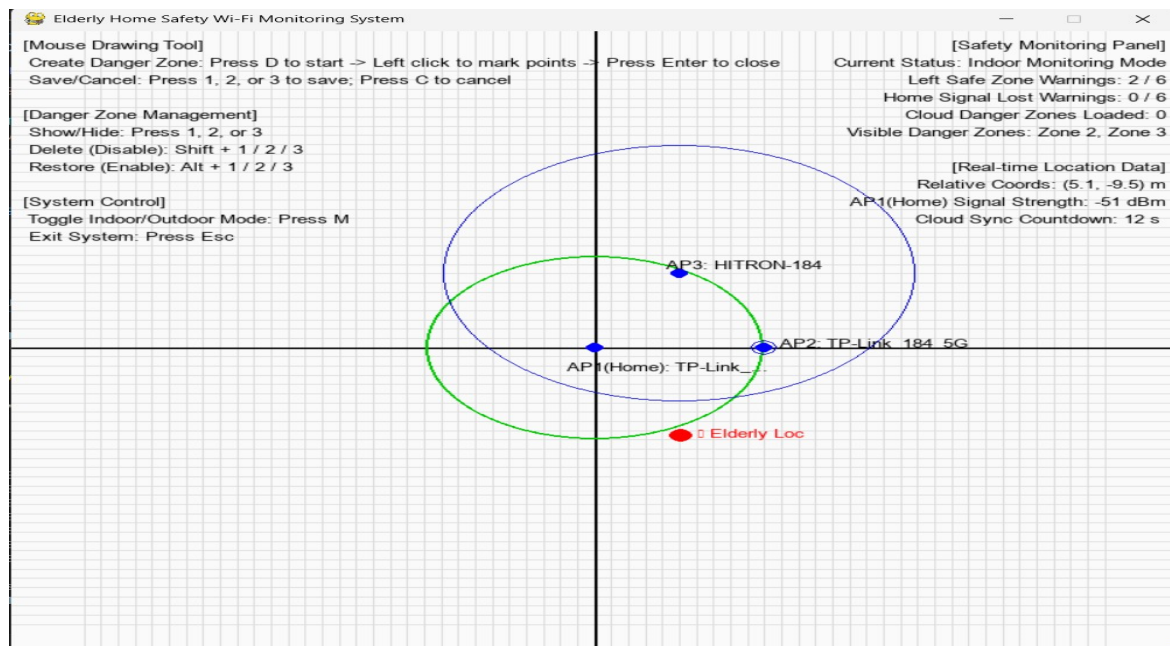


Figure 22. Outdoor mode switching based on insufficient Wi-Fi access points (the blue and green circles represent the coverage of Wi-Fi access points and safe zones, respectively).

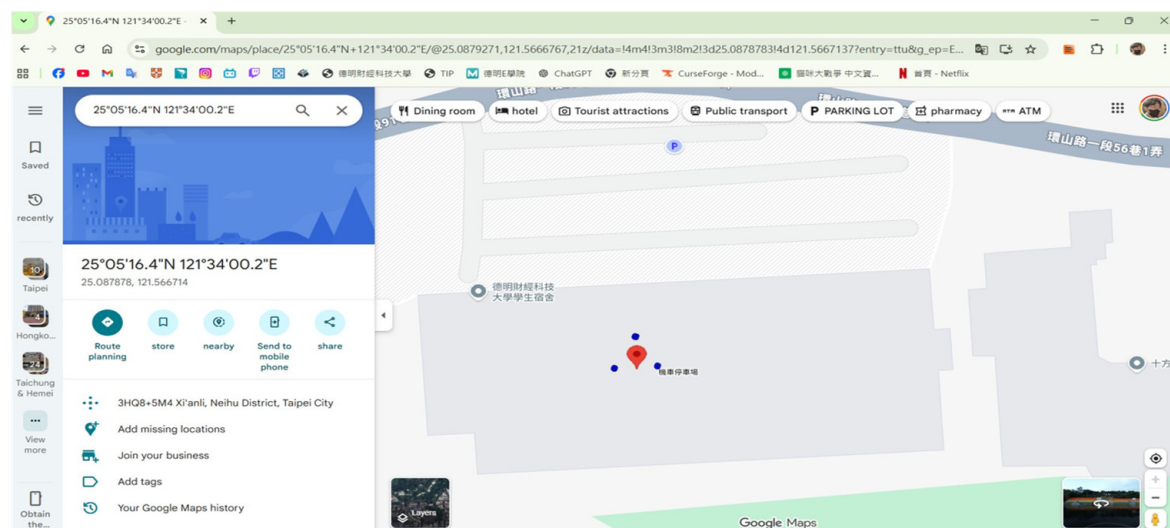


Figure 23. GPS-based outdoor localization displayed on Google Maps (the Chinese text in the map interface represents local geographic names and place markers in Taiwan).

4.5. Notification Subsystem

The notification subsystem delivers real-time safety and exercise alerts to caregivers. When the older adult enters a predefined dangerous area, an immediate alert is sent via Discord. If the older adult remains outside the safe zone for six consecutive detections, a warning message with a Google Maps link is also delivered as shown in Figure 24. In addition, the system monitors accumulated exercise calories during training sessions. When the predefined exercise target is reached, an exercise achievement notification is sent to caregivers via Discord. Google TTS is used to generate voice alerts for both location-related events and exercise target achievement, enhancing user awareness and motivation. The schematic as shown in Figures 25–27.

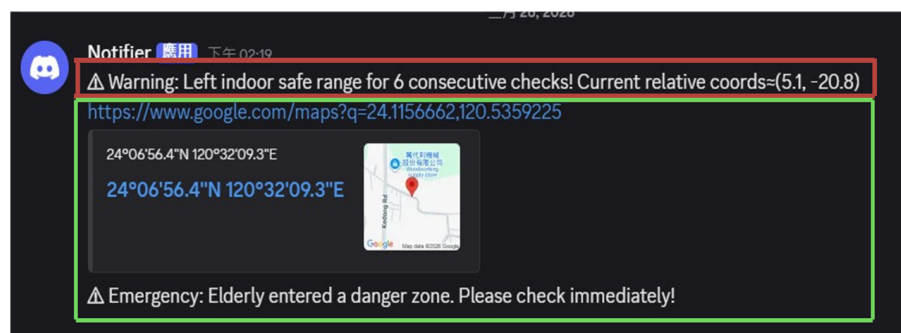


Figure 24. System alerts on the Discord interface. (a) Red box: danger zone intrusion alert; (b) green box: automated location sharing after consecutive perimeter breaches (the non-English UI labels represent standard Discord and map system interface tags).

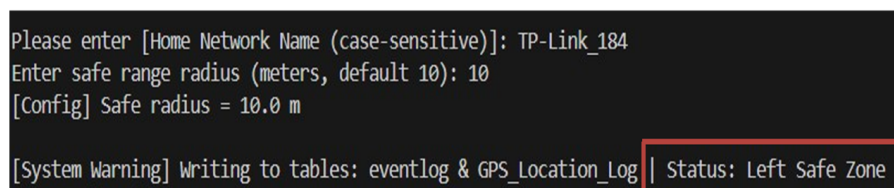


Figure 25. Voice alert for leaving the safe zone.

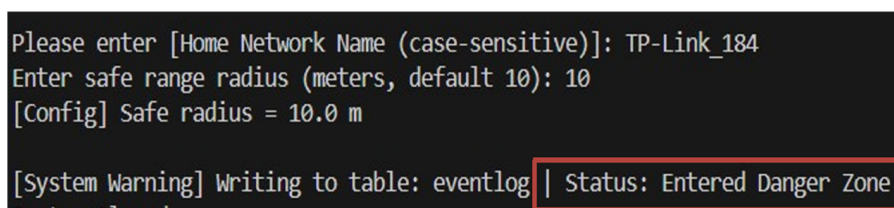


Figure 26. Voice alert for entering a dangerous area.

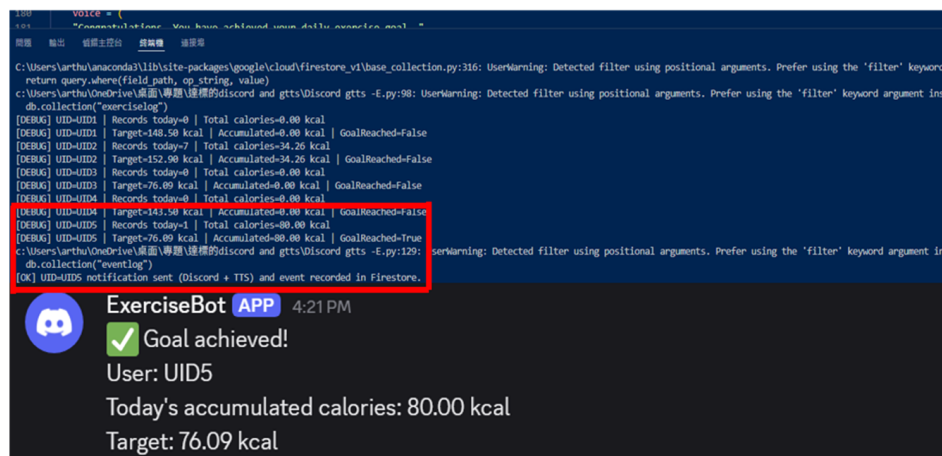


Figure 27. When the exercise target is reached, a notification is sent using Discord, and a voice notification is played (the non-English path names in the console represent local system directory names and do not affect the execution logic).

4.6. Query Subsystem Interface

Caregivers can access the web-based interface to review real-time and historical data of the older adult. The system retrieves data from the Firebase cloud database and displays exercise records, location information, and system events in a graphical and tabular format. This interface enables caregivers to conveniently monitor the health and safety status of the older adult. The schematic is shown in Figures 28 and 29.

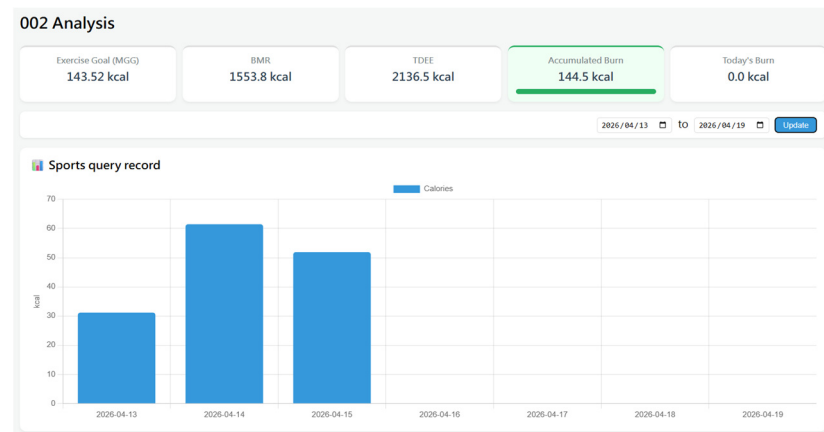


Figure 28. Exercise data analysis interface for daily calorie consumption and target comparison for Example 1.



Figure 29. Exercise data analysis interface for multi-day goal achievement comparison for Example 2.

5. Conclusions

An integrated elder care and health monitoring system is developed by combining wearable sensing, vision-based motion recognition, and dual-mode localization to support daily exercise supervision and safety management for the elderly. The health exercise subsystem employs three-axis accelerometers and a camera-based motion recognition module to monitor posture and movement accuracy in real time. By analyzing motion trajectories and exercise patterns, the system provides immediate feedback, thereby improving exercise quality and reducing injury risk. Sensor and camera data are transmitted to the computing subsystem, processed, and visualized through a web-based interface that displays exercise status, accumulated calories, and motion trajectories. Exercise records are stored in the Firebase cloud database, enabling long-term tracking and retrospective analysis. For location awareness, the localization subsystem integrates Wi-Fi-based indoor positioning with GPS-based outdoor tracking, automatically switching between modes according to the number of detected Wi-Fi access points. Safe zones and hazardous areas are predefined, and alerts are triggered when users leave safe zones or enter dangerous areas. The notification subsystem delivers these alerts through Discord and Google TTS, ensuring caregivers are promptly informed and able to intervene. All location events and notifications are logged in the Firebase database for subsequent review. The database subsystem manages caregiver accounts, personal data, exercise records, localization data, and event logs, providing a comprehensive framework for scalability, historical analysis, and future intelligent health analytics. By integrating these subsystems, the system enables

continuous monitoring of exercise performance and location status, supports informed decision-making for caregivers and older adults.

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Conflicts of Interest: The authors declare no conflict of interest.

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