D2.5 - Pilot use case: mobility disorder patient monitoring, implementation and training

Work package	WP2
Task	Task 2.5
Due date	9th September 2024
Submission date	3rdst October 2024
Deliverable lead	UNN and MFU
Version	0.1
Authors	UNN team (Nauman Aslam, Shanfeng Hu, Neera Jeyamohan,), MFU (Worasak Rueangsirarak, Punnarumol Temdee, Surapong Uttama) and CMU (Dorn Pradorn, Liu Xin)
Reviewers	Timo De Waele (UGent)

Table of Contents

List of Figures

List of Tables

Executive Summary

This report outlines the outcomes of two pilot cases aimed at preventing falls among older adults using digital health technologies and mobility monitoring systems. Conducted at Chiang Mai University (CMU) and Mae Fah Luang University (MFU), these pilot projects focus on early intervention through fall-risk assessment and personalized health promotion, with the goal of reducing fall-related accidents in the elderly.

Stakeholder workshops in Chiang Rai and Chiang Mai emphasized the importance of focusing on the promotion and prevention stages of healthcare. These workshops helped shape both pilot cases to address the early risk factors associated with falls, emphasizing early-stage interventions that prevent the need for more extensive treatments later in life by Fried et al. (1998) [13].

Pilot Case 1: Elderly Exercise and Fall Prevention at CMU

The first pilot case at CMU introduced a mobility monitoring and exercise system designed to enhance fall prevention. Using wearable devices, AI-driven data analysis, and real-time feedback, the system provided elderly participants with personalized exercise routines. Tools such as smartwatches and motion analysis dashboards monitor heart rate, movement, and exercise intensity based on the FITT principles (Frequency, Intensity, Time, and Type).

Healthcare practitioners played a key role in ensuring the system's effectiveness by adjusting routines in real time to suit each participant's physical capabilities. This approach not only improved physical health but also promoted independence among the elderly, allowing them to actively monitor their own progress. Insights from this pilot will be crucial in refining the system's data analysis capabilities and expanding its use to more elderly care settings, contributing to improved quality of life through active aging.

Pilot Case 2: Fall-Risk Assessment at MFU

The MFU pilot case focused on an integrated fall-risk assessment system, which helps healthcare practitioners evaluate the mobility and fall risks of elderly individuals. This assessment guides caretakers in providing appropriate interventions such as exercise or treatment. The system, which includes hardware and software, was structured into IoT, edge, and server layers that securely transmitted data through a Wi-Fi network.

The pilot took place in the Nanglae community, involving 33 seniors in five experiments. With the collection of 308 data records, the system applied machine learning models that achieved an impressive 98.7% classification accuracy in identifying fall risks. Although there are some limitations, this pilot demonstrated the potential for using smart technologies to improve fall-risk assessments. Continued research and data collection will help further refine the system, ensuring it becomes a more effective tool in fall prevention.

Both pilot cases underscore the success of collaboration between healthcare professionals, technology developers, and research institutions in addressing fall risks among the elderly. The projects demonstrated the transformative potential of digital health technologies in preventing falls and improving elderly care. The insights and innovations from these pilots pave the way for expanded applications, broader adoption, and ongoing research aimed at promoting active aging and enhancing quality of life for older adults in Thailand and beyond.

1 Introduction

At the onset of our project, the consortium recognized the significance of engaging with stakeholders to understand the need for digital healthcare and monitoring systems, particularly for elderly care, in their respective countries by Allaire et al. (2013)[2], Kawashima et al. (2008) [22]. This led to the organization of two insightful workshops, hosted by MFU and CMU in Chiang Rai and Chiang Mai, respectively. These workshops, which involved key stakeholders, underscored the importance of focusing on the promotion and prevention stages of healthcare, particularly in the context of reducing fall risks among the elderly.

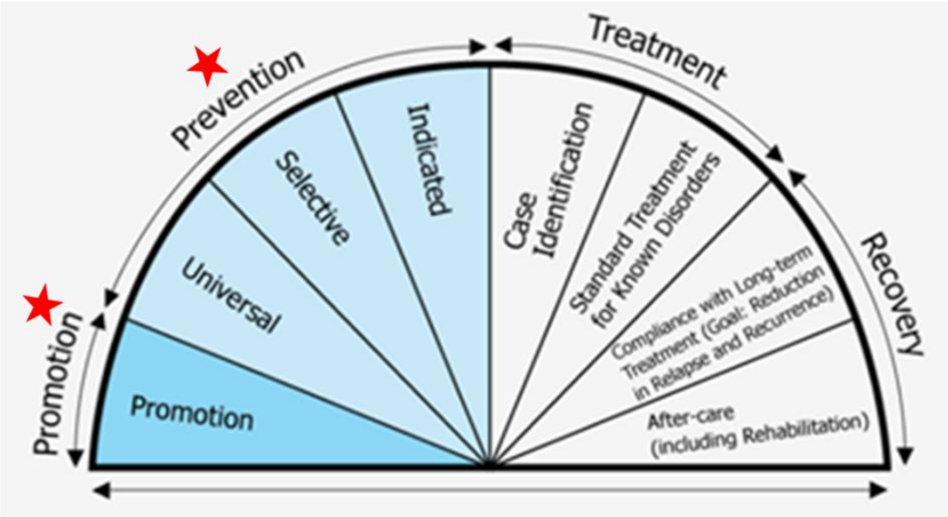


Figure 1: Behavioral Health Continuum of Care Model. By W. H. Organization (2007) [39]

In the promotion stage, the focus was on informing the elderly and their caregivers about the benefits of physical activity and how maintaining mobility can prevent falls by Rockhill et al. (2001)[26], Sandvik et al. (1993)[27]. Both MFU and CMU worked together to introduce elderly participants to personalized exercise routines designed to enhance physical health and reduce fall risks. This proactive approach empowers elderly individuals to maintain an active lifestyle, which can prevent the decline in mobility that often leads to falls by Prasert (1979)[1].

In the prevention stage, the collaboration between MFU and CMU was crucial in developing systems that help detect early signs of mobility decline or fall risk. The pilot cases employed wearable devices and AI-driven data analysis to monitor participants' movements, heart rate, and exercise intensity in real time by WHO (2007)[39]. Healthcare practitioners from both universities were able to adjust exercise routines to suit each participant’s capabilities, thereby reducing the likelihood of falls and preventing more severe physical issues.

By focusing on both promotion and prevention in these pilot cases, the joint efforts of MFU and CMU aim to establish a comprehensive mechanism for fall-risk reduction, which is critical to improving the overall quality of life for the elderly population.

In Pilot Case 1 at MFU, we will be focusing on studying the standard assessment for elderly performance to identify early-stage problems with falling. And in Pilot Case 2 at CMU, we will study to implement an exercise monitoring system for elderly individuals in care homes, using real-time data to track and improve physical activity. Both pilot cases will be integrated into the healthcare model's prevention stage, ensuring a comprehensive approach to fall risk identification and exercise monitoring.

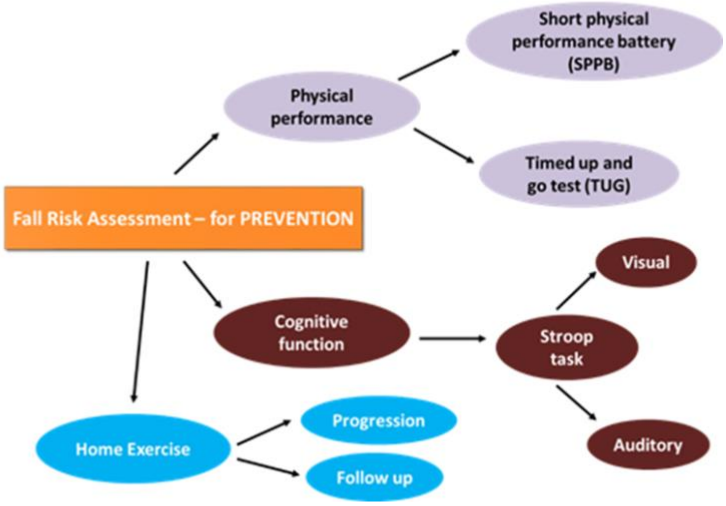


Figure 2: Falling risk assessment tools

From Figure 2, Physical Performance and Home Exercise are selected as the falling risk assessment tools to be improved upon for preventing patients from falling in the Thailand use case. Physical performance is the primary method for identifying the risk of falling in humans by leveraging the risk of falling using the short physical performance battery (SPPB) criteria. Together with a clinical tool such as the Timed Up and Go Test (TUG), these methods are recommended to determine physical body balance by Barnett et al.(2003)[3]. These two measurement tools can present the important factors associated with human falls. For home exercise, this tool is a mechanism for encouraging the elderly to continue practicing on the assigned recovery program to keep the early-stage factors from falling under control. Following up the participants using a mobile-based application can collect the progression of the participant's workout to meet the symptom rehabilitation.

This pilot case is a testament to the power of collaboration. It involves the development of a mobility disorder monitoring system, a joint effect between MFU and CMU. This collaborative spirit is further reflected in the system architecture, as illustrated in Figure 3. MFU's focus on fall-risk assessment at healthcare centers, combined with CMU's intention to monitor the elderly's activities and exercises at home, showcases the strength of unity in tackling healthcare challenges.

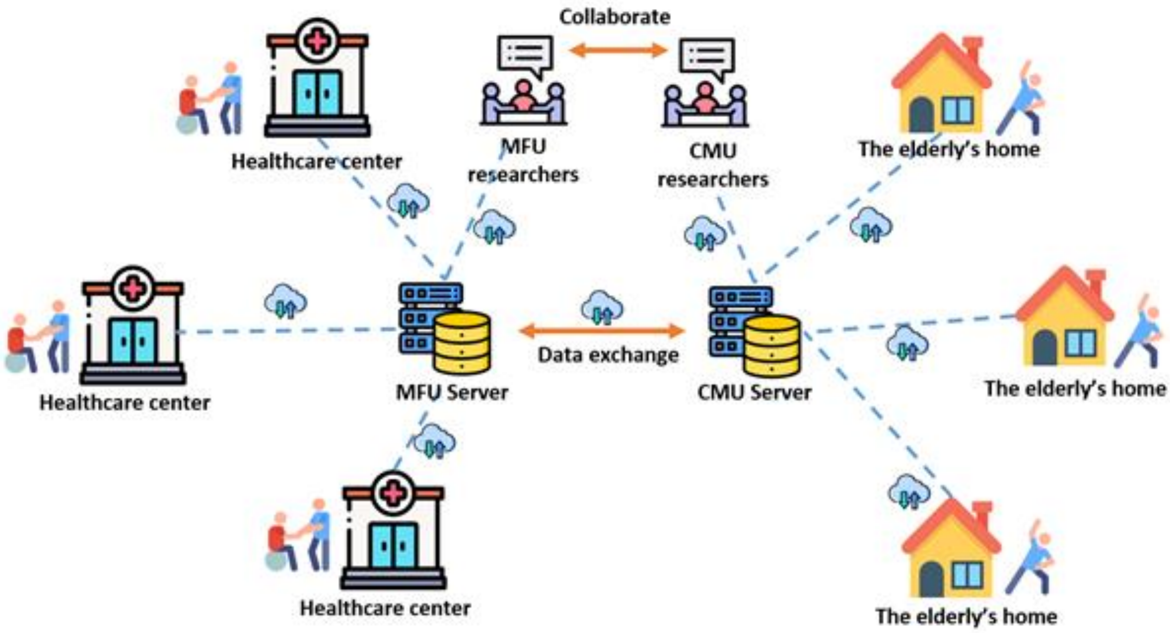


Figure 3: Mobility disorder monitoring system's architecture in Pilot Case 2 by MFU and CMU

2 Pilot Case Implementation at CMU

2.1 Introduction

The pilot case implementation at Chiang Mai University (CMU) marks a significant milestone in our research project focused on elderly exercise equipment for fall prevention. This section provides an overview of the design, methodology, and key components involved in the implementation process. Through collaboration with healthcare practitioners and rigorous planning, we aim to leverage advanced technology and data analysis to enhance the well-being of elderly individuals in our community. From system design to data collection strategies, each aspect of the pilot case implementation is meticulously crafted to ensure effectiveness and efficiency in achieving our research objectives. Let's delve into the details of our approach and the steps taken to bring this project to fruition.

2.2 System Architecture

2.2.1 Introduction

When designing a user interface (UI) for elderly, it is critical to conduct thorough UX experiments to understand their specific needs, limitations, and preferences. This research was conducted to ensure that the final system design would be accessible, usable, and effective for elderly users, particularly those participating in the project. The experiments focused on key areas such as color perception, font readability, and interaction methods. These experiments were designed to gather data on how elderly users interact with the system, ensuring that the interface can accommodate their cognitive, visual, and physical abilities.

2.2.2 Gather Information about UX/UI Development

In preparation for the UX/UI design for elderly users, a thorough review was conducted to understand the specific visual, physical, and cognitive challenges faced by this demographic. This preliminary information gathering aimed to identify design elements that would make the system accessible, intuitive, and easy to navigate for elderly users. Key factors examined included color preferences, font characteristics, interaction methods, and cognitive navigation support.

Color Preferences for Readability

Studies indicate that color perception changes with age, often affecting the ability to distinguish certain color contrasts. To address this, we conducted a vision test focused on identifying optimal background and foreground color combinations for elderly users. Results showed that elderly individuals could read text more effectively on warm background colors compared to cool ones, as seen in the RGB color spectrum. This insight guided the design choice to prioritize warm colors in the interface to improve readability.

Font Characteristics: Size and Style

Font size and type significantly impact readability for elderly users. Our review included examining the legibility of Serif and Sans Serif fonts at various sizes, from 100 points down to 5 points, to determine which combination provided the best readability for older adults. Findings showed that larger Serif fonts were easier for elderly users to read, reinforcing the decision to use larger font sizes and Serif typefaces in the interface design.

2.2.3 Interaction Experiments

Interaction preferences were reviewed to determine the most intuitive methods for elderly users to navigate the system. Two types of interactions were considered:

Hands-on Interaction: Research indicated that elderly users performed better with hand gestures that involved a simple "hand stroke" for selecting options. Additionally, static scrolling selectors were more manageable, as they minimized errors and provided greater control. This guided the inclusion of a hand stroke gesture and a stable scrolling mechanism in the design.

Body Gestures: For body-based interaction, both static and dynamic gestures were reviewed. Findings indicated that elderly users found static gestures, such as the Arm to Side Gesture, easier and more comfortable than dynamic ones. Consequently, the interface was designed to favor static body gestures to enhance ease of use.

Cognitive Navigation and Menu Structure

Elderly users often have limitations in memory retention, which can impact their ability to navigate deep menu structures. Based on cognitive studies, the design was oriented towards a simplified, less hierarchical menu structure, enabling users to locate information and navigate options without confusion. This structure supports cognitive accessibility by reducing the mental load required to interact with the system.

Conclusion: Key Insights for UX/UI Design

The insights gathered from this review were integral in shaping the initial design guidelines for the research study by Suwan et al. (2020) [31]. Key design considerations based on these findings include:

Color: Prioritizing warm background colors for enhanced readability.

Font: Using larger, Serif fonts to aid legibility.

Interaction: Implementing hand stroke gestures and static body gestures for intuitive navigation.

Cognitive Support: Designing a simplified menu structure with fewer hierarchical layers to accommodate memory limitations.

2.2.4 Collect Exercise Posture Information

From researching information on exercise for the elderly. It was found that muscles can be developed in both the upper and lower parts of the body. Exercise can be divided into 5 phases: warming up the body, stretching, exercising, holding on, and cooling the body down. The duration of exercise can be 150 minutes per week. or not less than 30 minutes per day, 3 -5 days per week, etc., and the intensity of exercise must not be harmful to the health of the elderly. Therefore, we can design exercise postures for the elderly using arm and leg positions. According to research Leg postures are divided into 9 grids with 9 different steps and 21 arm positions in aerobic exercise, and are divided into easy, medium, and difficult, with the designated song being a song with a beat/ value. min and different exercise durations by Huang & Ferris (2004) [16].

2.2.5 Exercise Assessment Reviews

The process of gathering data on physical fitness and improving it among the elderly is essential for ensuring their safety during exercise. Various methodologies are utilized to evaluate and enhance the physical fitness of older adults. These data are then combined with exercise routines and various formulas to summarize the outcomes of physical fitness assessments before elderly individuals begin exercising. The primary goal of physical fitness assessments in the elderly is to predict their capacity for daily activities and the likelihood of dependency on others by Kamitani et al. (2013) [19]. These assessments encompass two main categories: health-related fitness and athletic ability. Health-related fitness covers aspects like cardiopulmonary endurance, muscular strength and endurance, muscular flexibility, and body composition, while athletic ability includes factors such as speed, agility, balance, coordination, reaction time, and power. Assessing physical fitness is crucial for assessing the risks before engaging in physical activities or exercise programs, devising exercise plans, establishing objectives, and encouraging elderly individuals to participate in physical activities. Before assessment, older adults are screened for safety, and pretest instructions are provided to avoid any complications. Emergency procedures should also be in place in case of emergencies during assessments by Ballesteros et al. (1965)[5].

The investigation into fitness testing and health promotion for the elderly entails gathering preliminary data and consulting with experts. Most elderly individuals possess a good understanding of their mobility potential, making tests focusing on walking or movement less influenced by exercise. Before participating in exercise sessions, doctors assess vital signs such as blood pressure, blood oxygen levels, and heart rate to ensure safety. Additionally, questionnaires designed to evaluate fitness levels and enhancement needs are employed, with doctors offering personalized advice based on the results.

2.2.6 UX/UI Design for the Elderly

2.2.6.1 Introduction

This section focuses on designing a user interface (UI) tailored for elderly users, ensuring it meets their unique needs. The goal is to create an intuitive, accessible design that considers the physical and cognitive challenges of aging, such as visual impairments, reduced motor skills, and cognitive decline. Through collaboration with UX/UI designers and elderly participants, we aim to develop a user interface that promotes ease of use and inclusivity in exercise systems.

2.2.6.2 Methodology

The design process involved several key activities to ensure the user interface (UI) was accessible and user-friendly for elderly participants, particularly considering their cognitive and physical limitations.

Conducting a Detailed User Analysis

Objective:
To thoroughly understand the specific needs and preferences of elderly users, especially those with visual, cognitive, and motor impairments.

Activities:

1. **Leverage Existing Insights:** The analysis was guided by earlier research on the limitations experienced by elderly users, focusing on the challenges posed by aging, such as reduced visual acuity, declining cognitive function, and decreased motor control.
2. **Consider Key Factors:** The analysis accounted for important aspects, including cognitive abilities, visual acuity, and motor skills. These factors were crucial in designing a UI that is easy to use, considering that elderly users may have difficulty navigating complex systems or reading small text.
3. **Collect Feedback from Participants:** Feedback was gathered through surveys, interviews, and usability testing with elderly participants. This helped capture a range of perspectives, as participants varied in age and visual impairments (e.g., long-sightedness, short-sightedness, and blurred vision). This feedback provided a comprehensive understanding of their requirements for a user-friendly interface.

Collaboration with UX/UI Expert Designers

Objective:
To create an intuitive, accessible interface specifically tailored to the needs of elderly users, ensuring that the design addresses common challenges related to aging.

Activities:

1. **Collaborative Sessions:** UX/UI designers participated in collaborative workshops where insights from the user analysis were shared. This allowed designers to better understand the elderly users' needs and limitations, such as difficulty reading small text or interacting with cluttered interfaces.
2. **Consider Unique Challenges:** Designers were encouraged to consider the unique challenges faced by aging users, particularly in terms of legibility, ease of navigation, and the need for a simple, uncluttered interface. The design philosophy aimed to minimize cognitive load, ensuring that users could navigate the system without confusion or frustration.
3. **Fostering Inclusivity:** The design philosophy prioritized inclusivity, meaning that accessibility features, such as voice commands and larger touch targets, were considered to accommodate users with varying levels of physical and cognitive abilities.

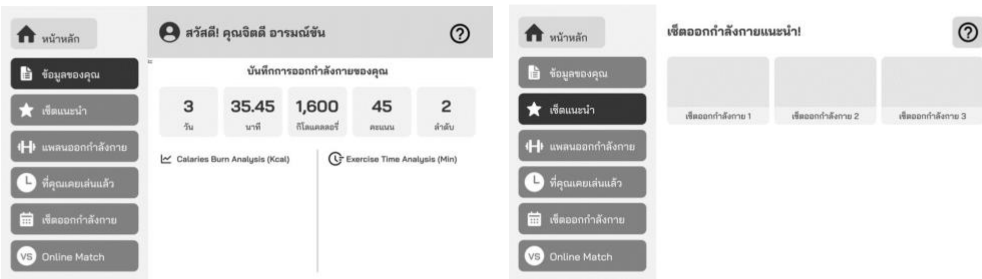


Figure 4: Draft User Interface Design (White, Gray, Black)

Experiments in UX/UI Design

Following the detailed analysis and collaboration with UX/UI designers, we proceeded with experiments focusing on UI design testing for elderly participants. These experiments were aimed at evaluating different color schemes and design formats to ensure that the UI would be both accessible and visually comfortable for elderly users.

Objective:

Tailor the user interface of the system to facilitate ease of use for elderly individuals, ensuring the design supports exercise activities and everyday interaction.

Activities:

1. **Experiment with Color Schemes**: We tested four different color schemes to determine which colors promoted the most visibility, contrast, and user comfort. These colors were tested based on the preferences of elderly users, focusing on maximizing readability and reducing eye strain. The colors tested were:
   - **Design A: Green** (*Figure 5*)

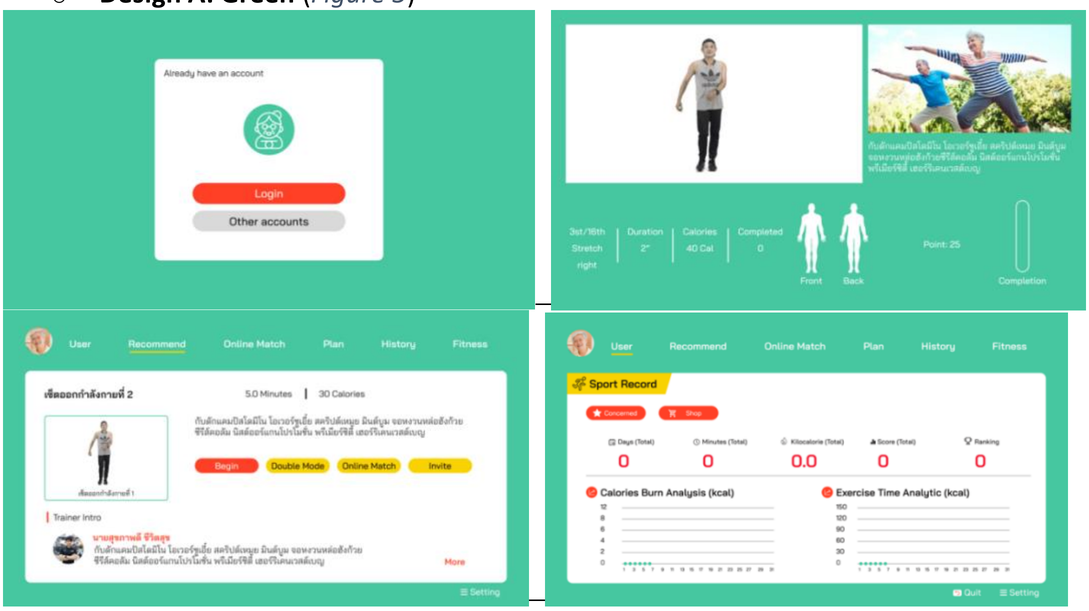


Figure 5: Green UI Design

   - **Design B: Orange** (*Figure 6*)

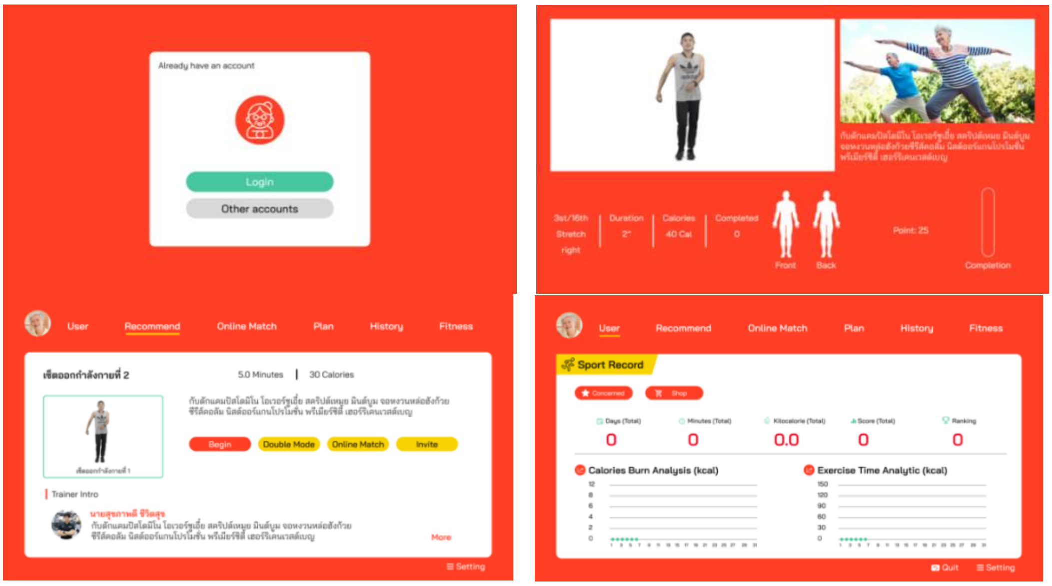


Figure 6: Orange UI Design

- **Design C: Blue** (*Figure 7*)

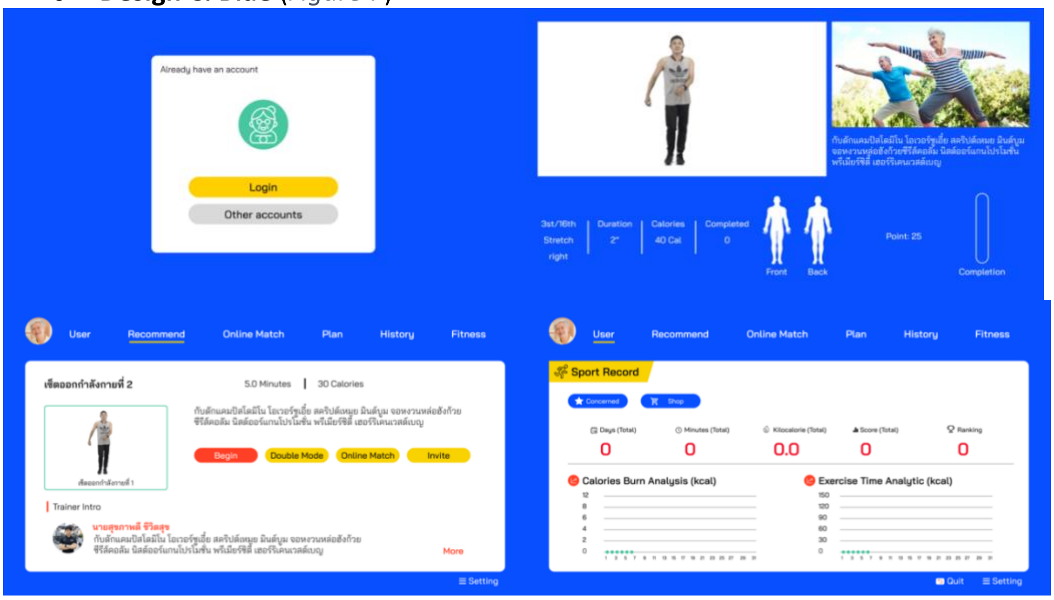
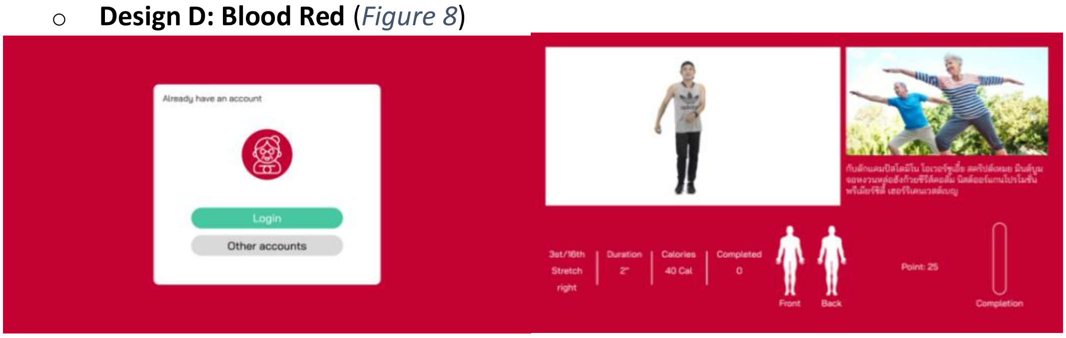


Figure 7: Blue UI Design

- **Design D: Blood Red** (*Figure 8*)



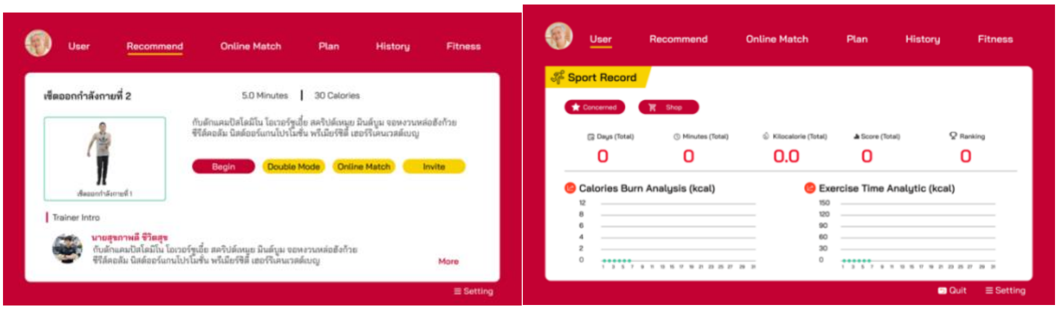


Figure 8: Blood Red UI Design

2. **Evaluate Design Formats**: The design formats included variations in navigation elements, font sizes, and button placements to enhance ease of interaction. Each format aimed to minimize the complexity of the interface while maximizing efficiency. Special attention was given to simplifying menus and interactions, allowing elderly users to navigate without confusion or requiring excessive memorization by Swinnen (2002) [32].
3. **Gather Feedback through Iterative Testing**: We conducted multiple rounds of testing with elderly participants, where each color and format was evaluated for its clarity, ease of use, and overall user satisfaction. The feedback from these sessions was essential in refining the designs, ensuring that the interface was as intuitive and accessible as possible.

User Interface Design Test Results

Objective:

To gather quantifiable data on user preferences for the different UI designs, based on color scheme, layout, and overall usability, with a particular focus on ease of visibility for elderly users.

Participants:

Sixteen elderly participants were selected to test the various UI designs. They varied in age, gender, and visual impairment (e.g., long-sightedness, short-sightedness, blurred vision due to surgery). Each participant was asked to rate the UI designs on a scale, with lower scores indicating a higher preference.

Test Results:

The following table summarizes the user ratings for the different UI color schemes:

Table 1: User Interface Test Results (Lower score = Liked more I Higher score = Liked less)

User	Gender	Age	Visual Impairment	A	B	C	D
1	Female	68	Long-sighted	5	2	3	1
2	Female	68	Long-sighted	4	3	2	1
3	Female	74	Long-sighted	1	4	5	2
4	Female	65	Short + Long-sighted	5	4	1	2
5	Male	65	Short-sighted	3	2	5	1
6	Female	74	Short + Long-sighted	5	3	4	1
7	Female	63	Long-sighted	5	2	4	3
8	Female	62	Surgery-induced 100% blurred vision	2	1	5	3
9	Male	67	Long-sighted	5	2	4	1
10	Female	77	Long-sighted	5	1	3	2
11	Female	64	Long-sighted	5	1	4	2
12	Female	64	Short-sighted	1	3	5	4
13	Male	73	Short + Long-sighted	4	1	3	2
14	Female	64	Long-sighted	5	3	1	2
15	Female	74	Long-sighted	5	3	4	1
16	Female	81	Long-sighted	5	4	2	1
Total				65	39	55	29

Summary of Results:

- **Design A (Green)**: Received a total score of 65, indicating a lower preference compared to other designs. The green color may have been less effective in providing clarity and contrast.
- **Design B (Cyan)**: Received a score of 39, making it one of the top choices for elderly users. Its high contrast and pleasant hue contributed to positive feedback.
- **Design C (Blue)**: Scored 55, indicating a moderate preference. Some participants found blue to be comfortable, but it was not as widely favored as cyan or blood red.
- **Design D (Blood Red)**: Received the lowest score of 29, indicating the highest preference. The strong contrast and visibility of this design made it ideal for elderly users with vision impairments.

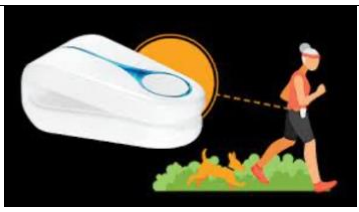
Compare Standards for Designing Models of Care for the Elderly

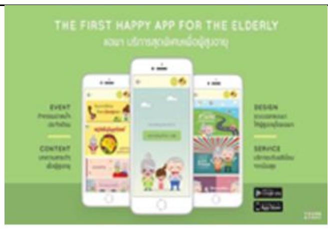
When comparing standards for designing models of care for the elderly, it is essential to assess both the technology developed within our research project and the existing standards within the field. This comparison sheds light on innovative approaches and best practices aimed at enhancing elderly care. Our analysis encompasses various aspects such as the format of storage systems, utilization of technology, and strategies for promoting well-being among the elderly by Nimit-arnun (2021) [24].

To comprehensively evaluate standards for designing models of care for the elderly, it is imperative to introduce another technology table highlighting the features of both the technology developed within our research project and the established standards in elderly care. These tables serve as valuable tools for identifying key differences, strengths, and areas for improvement in both approaches. Through this comparative analysis, we aim to gain insights into the effectiveness and applicability of different care models for the elderly.

Table 2: Comparison of technologies

Technology topic.	Technology Detail.	How to apply or deploy to this project.
Developing the format of the storage system	 Technology that uses "Big Data" to help analyze and store data.  Smart Wristband for Elder is a device that uses IoT (Internet of Things) technology and sensors.	Technology that uses "Big Data" to help analyze and store data. **Application to the project:** The storage system will leverage Big Data technology to store and manage the vast amounts of data collected from the Smart Wristband for Elder. This wristband collects real-time health and exercise data, which will be transmitted and stored securely in a cloud-based storage system. **Integration:** The integration of the wristband data with the storage system allows physical therapists to access and analyze the information, providing a complete overview of the elderly users' health and exercise progress. **Usage:** This data is then used to track long-term trends, monitor the effectiveness of exercise routines, and adjust care plans as needed. The system also enables easy sharing of this information between caregivers and healthcare professionals for better decision-making.
A good model for reducing depression problems among the elderly.	 Elderly robot companion helps reduce loneliness and depression.	**Robots are not used in this project:** Instead, the focus is on developing accessible, low-maintenance exercise equipment that elderly users can easily use and install themselves. This equipment is designed to promote independence and reduce the need for external maintenance or assistance. **Exercise equipment for social interaction:** The system is designed to encourage elderly

	 Robots promote the development of autistic children. It is designed to be a friend to relieve loneliness for the elderly. and help facilitate the care of the elderly for their children	users to come together in groups, forming a social community that helps combat loneliness and depression. By facilitating group activities, the project creates a supportive environment for elderly participants. **Dance and exercise programs:** The equipment supports both individual and group exercises, such as dancing, which has been shown to improve physical and mental health. Group dance sessions allow users to engage in enjoyable physical activity while socializing with others. **Application-based support:** The system integrates with a research application developed as part of this project. Through the app, elderly users can track their exercise routines, receive feedback, and share their progress with physical therapists and peers. **Variety of exercise programs**: The project includes several different types of exercise routines, all of which have received positive feedback from users. These programs are designed to meet the physical needs and capabilities of elderly participants. **Ease of use:** Elderly users can easily learn how to install and use the equipment, with user-friendly instructions and intuitive interfaces. This ensures that the system is accessible to a wide range of users, regardless of their technical ability.
Elderly fall detection system		The smart brooch is a wearable technology designed for elderly care, both inside and outside the home. It is worn around the neck and can detect falls, sending notifications when necessary.

	The smart brooch is a technology for caring for the elderly both inside and outside the home.  Hanging from the neck for the elderly or sick that can detect and notify of falls.	**Current Status:** The smart brooch is still in the development phase and requires further testing in the market. It is not yet compatible with other devices or systems in the project. **Cost and Market:** As a prototype, this technology is relatively expensive and has undergone limited market testing, which needs to be addressed before full integration into the project. **Application to the Project:** While the smart brooch focuses on fall detection, the technology developed in the project aims to prevent falls by promoting strength-building through exercise. The goal is to reduce fall risks before they occur, rather than relying solely on detection after the fact. **Long-Term Goal:** The project will develop a system that empowers the elderly to increase their physical strength, allowing them to better care for themselves and minimize the chances of falls over time.
Forms of care for the elderly and help the elderly work	 Application to connect services to create activities and provide welfare to the elderly	- There is a service model that uses software, but there is a lack of hardware to strengthen the body and has not yet made the system into a social communication system. To allow the elderly to meet each other like the technology developed in the project
Standards for care for the elderly with a complete marketing model	 home care system Management system for monitoring and caring	- Partners that can work together in the future This is because this form of organization still lacks the addition of technology to help improve management and development of various parts. - This technology does not have an exercise assistance system like the

	for the health of the elderly in communities in Chiang Mai Province	one developed in the research project. - It is a new alternative channel to use the technology developed in the research project to be supplemented with comparative technology.

The comparative analysis of various technologies reveals their potential applications in eldercare, ranging from data analysis to fall detection. However, our research project aims to develop an integrated exercise platform tailored to the needs of the elderly. Leveraging insights from these technologies, we envision a comprehensive solution that combines hardware and software to facilitate easy use, foster social interaction, and promote physical activity. This platform will address key challenges in elderly care while enhancing overall well-being and independence.

Research Review on Exercise Program Design for Physical Fitness

Designing an effective exercise program requires focusing on key aspects that contribute to physical health and fitness. According to multiple research studies, including recommendations by the American College of Sports Medicine (ACSM) and other scholars, a well-rounded exercise program should incorporate the following elements:

1. **Warm-Up**: Warming up prepares the body for physical activity by increasing heart rate, blood flow to muscles, and joint mobility. A proper warm-up should last approximately 10 minutes and gradually increase in intensity to avoid injury.
2. **Endurance Training**: Endurance or aerobic training is vital for improving cardiovascular health and lung capacity. Studies recommend that endurance training should be performed for 20-60 minutes, 3-5 times per week, at 60-70% of the individual's maximum heart rate. This type of training not only builds cardiovascular endurance but also helps increase overall stamina and muscle endurance.
3. **Recreational and Relaxation Activities**: Incorporating recreational activities into an exercise program helps maintain motivation and provides enjoyment, which is crucial for long-term adherence. Additionally, relaxation exercises or cool-down periods (5-10 minutes) at the end of a session allow the body to recover and prevent muscle stiffness.
4. **Flexibility Training**: Flexibility exercises should be a part of both the warm-up and cool-down phases. Regular flexibility training enhances joint mobility, muscle elasticity, and range of motion, reducing the risk of injury during more intense exercises.

Principles of Exercise Program Development

The development of an exercise program is guided by the FITT principles, which stand for Frequency, Intensity, Time, and Type. These principles, as outlined in multiple studies by Giam and The (1988) [15]; Johnson (1985) [17]; Chusak Wechaphaet (1995)[9], provide a framework for designing programs tailored to different fitness goals, particularly for elderly individuals. Below is a review of the FITT principles:

1. **Frequency (F)**: The frequency of exercise sessions per week is critical for maintaining fitness. Research suggests that lung and heart endurance training should occur 3-5 times per week, with no more than two consecutive days off. For flexibility or muscle strength training, exercising 2-3 times per day may be necessary for optimal results.
2. **Intensity (I)**: Exercise intensity, often measured by the percentage of maximum heart rate, determines how hard the body works during physical activity. For older adults, studies recommend a range between 40-80% of the maximum heart rate, with

significant fitness improvements observed at just 40-50% intensity. To enhance endurance, maintaining a heart rate of 50-70% for 15-20 minutes is ideal.

3. **Time (T)**: The duration of each exercise session varies depending on the type of exercise. For aerobic activities, sessions lasting 15-60 minutes are recommended, while flexibility or strength exercises may require shorter durations (20-30 minutes) to be effective.
4. **Type (T)**: To achieve total fitness, a combination of different exercises is essential. The program should include activities that enhance muscle strength, flexibility, and cardiovascular performance. This variety ensures comprehensive physical fitness development by Woodard & Berry (2001)[37].

2.2.6.3 Conclusion

Based on research, the ideal exercise program for improving physical fitness—particularly in elderly individuals—should include a balance of aerobic, strength, and flexibility exercises. The program should be customized according to the individual's capacity, considering factors such as heart rate, endurance levels, and mobility. By adhering to the FITT principles, an exercise program can effectively promote total fitness and overall well-being.

2.2.7 Exercise Program Development

2.2.7.1 Introduction

Exercise programs vary in form, each with its unique principles of development distinct from FITT. These principles, outlined by Giam and Teh (1988)[15] (cited in Kornkan (1995)[23], encompass essential components:

Exercise programs vary in form, each with its unique principles of development distinct from FITT. These principles, outlined by Giam and Teh(1988) [15], encompass essential components:

1. **Frequency of Exercise (F):** The frequency determines how often one should exercise per day or week. For programs focusing on lung and heart endurance, it's recommended to exercise 3-5 times per week by Johnson (1985) [17], consistently without gaps exceeding two days. Ideal exercise days could be Monday, Wednesday, Friday, or Tuesday, Thursday, and Sunday by Kanokros (1987) [20]. Alternatively, for flexibility or muscle strength and endurance programs, exercising 2-3 times per day is suitable by Johnson (1985) [17].

2. **Intensity of Exercise (I):** Exercise intensity dictates the level of exertion. For older adults, an appropriate intensity falls between 40-80 percent of the maximum heart rate by Johnson, (1985) [17]. Even individuals with minimal initial capacity can significantly improve fitness by exercising at 40-50 percent of their maximum heart rate by Chusak Wechaphaet (1995) [9]. It's noted that exercising at 40 percent of the maximum heart rate can foster physical fitness by Giam and The (1988)[15]; Schwartz and Buchner, 1999: 143). Training at an intensity of at least 50 percent for 20-30 minutes enhances exercise endurance (Wirun, 1994: 46), with an optimal range for older adults being 50-70 percent of the maximum heart rate for 15-20 minutes.

3. **Time of Exercise (T):** The duration of each exercise session is crucial. The recommended duration varies depending on the type of exercise and the individual's fitness level. For aerobic exercises, sessions lasting 15-60 minutes are advised by Johnson (1985) [17], while flexibility or muscle strength and endurance exercises may require shorter sessions of 20-30 minutes by Wirun (1994) [36].

4. **Type of Exercise (T):** Total fitness is achieved through a combination of exercises targeting muscle strength, flexibility, and cardiovascular health by Simpson (1986) [30]. Therefore,

incorporating a variety of exercises is essential to ensure comprehensive fitness development.

1. **Frequency of Exercise (F):** The frequency determines how often one should exercise per day or week. For programs focusing on lung and heart endurance, it's recommended to exercise 3-5 times per week by Johnson (1985) [17], consistently without gaps exceeding two days. Ideal exercise days could be Monday, Wednesday, Friday, or Tuesday, Thursday, and Sunday by Kanokros (1987) [20]. Alternatively, for flexibility or muscle strength and endurance programs, exercising 2-3 times per day is suitable by Johnson, (1985) [17].

2. **Intensity of Exercise (I):** Exercise intensity dictates the level of exertion. For older adults, an appropriate intensity falls between 40-80 percent of the maximum heart rate by Johnson (1985) [17]. Even individuals with minimal initial capacity can significantly improve fitness by exercising at 40-50 percent of their maximum heart rate. It's noted that exercising at 40 percent of the maximum heart rate can foster physical fitness by Giam and Teh (1988) [15]; Buchner, 1999: 143). Training at an intensity of at least 50 percent for 20-30 minutes enhances exercise endurance, with an optimal range for older adults being 50-70 percent of the maximum heart rate for 15-20 minutes.

3. **Time of Exercise (T):** The duration of each exercise session is crucial. The recommended duration varies depending on the type of exercise and the individual's fitness level. For aerobic exercises, sessions lasting 15-60 minutes are advised by Johnson (1985)[17], while flexibility or muscle strength and endurance exercises may require shorter sessions of 20-30 minutes.

4. **Type of Exercise (T):** Total fitness is achieved through a combination of exercises targeting muscle strength, flexibility, and cardiovascular health by Simpson (1986) [30]. Therefore, incorporating a variety of exercises is essential to ensure comprehensive fitness

To achieve total fitness, you should use a combination of exercises that strengthen your muscles, increase the flexibility of muscles and joints, and improve the performance of the lungs and heart by Simpson (1986) [30] as follows:

1. **Isometric Exercise (Static Exercise):** Isometric exercises involve contracting muscles without movement. While effective for developing muscle strength, they are not ideal for improving joint flexibility or cardiovascular health. For elderly individuals, isometric exercises should be limited due to their impact on blood flow and potential to increase systolic blood pressure. These exercises strengthen muscles but do not significantly benefit flexibility or lung capacity.

2. **Isotonic Exercise (Dynamic Exercise):** Isotonic exercises involve movement with muscle contraction, making them more suitable for improving muscle strength, joint mobility, and heart health. This type of exercise, such as leg lifts or resistance-based movements, helps to improve flexibility in the joints by allowing movement through a full range of motion. It also supports cardiovascular health, as it requires sustained effort, which improves lung function and circulation. Therefore, isotonic exercises are beneficial for both muscle flexibility and heart-lung performance.

3. **Cardiorespiratory Fitness (Aerobic Exercise):** Aerobic exercises focus on improving lung and heart function by increasing oxygen supply to the muscles. Exercises like walking, swimming, or cycling enhance respiratory and circulatory performance, which are crucial for elderly individuals. These exercises also contribute to improved flexibility, as they involve dynamic movement of various joints. Additionally, aerobic exercises improve agility, balance, and muscle endurance, making them key for overall physical fitness by Balter & Zehr (2007) [6].

4. **Flexibility and Relaxation Exercises:** Flexibility exercises are specifically aimed at improving joint mobility and muscle elasticity. For elderly individuals, exercises like Tai Chi and yoga are excellent for enhancing flexibility and joint function while also contributing to better lung and heart performance through controlled breathing techniques. Stretching exercises performed during warm-up or cool-down phases help in maintaining joint health and preventing stiffness, ensuring that the body remains flexible and functional. Flexibility exercises are an essential complement to strength and aerobic exercises, promoting a balanced and healthy exercise routine.

2.2.7.2 Methodology

Exercise Formation Process

The creation of these exercises integrates a variety of movements for both arms and legs:

1. **Leg Exercise (Lower Body)**: A 9-grid system is used to create different walking patterns, which are categorized into easy, medium, and difficult levels based on expert consultation.

2. **Arm Exercise (Upper Body)**: Aerobic dance-inspired arm movements are developed and divided into:
   - Single-arm movements (5 variations).
   - Dual-arm synchronous movements (13 poses).
   - Dual-arm asynchronous movements (3 positions).

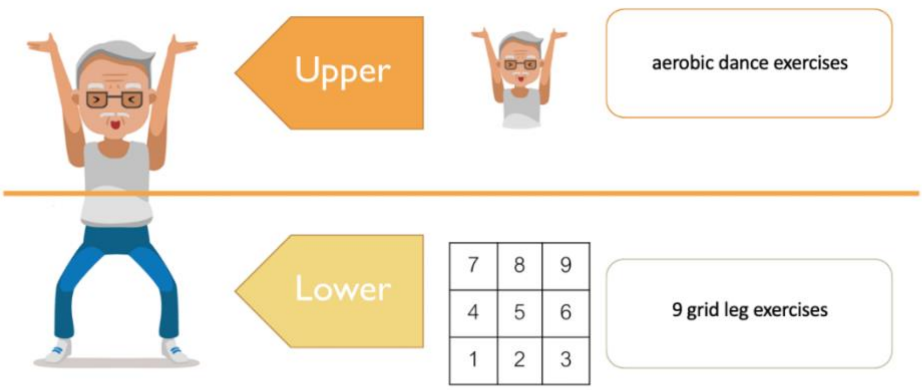


Figure 9: Posture design on upper posture using Aerobic Dance and Lower posture using 9-grid leg exercise

Participant Selection Process

To ensure the exercises are suitable for elderly participants, expert evaluations are carried out. The criteria for selecting participants include their mobility level, fitness capacity, and ability to follow the exercises without undue strain by Vidal et al. (2013)[34].

Testing and Evaluation

1. **Expert Evaluation**: Dance and elderly exercise experts evaluate the 9 leg poses and 21 aerobic arm poses to ensure they are safe and appropriate for elderly individuals.
2. **Pose Pairing and Analysis**: Leg and arm poses are paired together to form 189 possible combinations, which are then analyzed for compatibility.
3. **Level Classification**: Each pose combination is classified into easy, medium, and difficult levels to provide a structured exercise program that allows gradual progression.
4. **Testing Selection**: A balanced distribution of selected poses is tested for safety and efficacy, ensuring a wide representation of related movements.

2.2.7.3 Conclusion

The selected exercise postures undergo final evaluation, and a comprehensive diagram is generated to show the chosen poses and their relationships. This serves as a foundation for further testing and implementation, ensuring that the exercise routine is both effective and safe for elderly participants.

Table 3: Participant Demographics and Health Assessment

Number	Systolic (mmHg)	Diastolic (mmHg)	Criterion	Oxygen (%)	Heartbeat (bpm)	Doctor's Opinion (Allow)	Doctor's Opinion (Not Allowed)
1	156	85	Normal	97	72	✓	
2	125	74	Normal	99	66	✓	
3	143	86	Normal	80	79	✓	
4	190	100	High	97	71		✓
5	143	76	Normal	96	97	✓	
6	142	84	Normal	96	63	✓	
7	133	84	Normal	84	75	✓	
8	139	83	Normal	96	70	✓	
9	115	64	Normal	96	72	✓	
10	138	75	Normal	95	89	✓	
				Join Percentage		90%	10%

Upon reviewing personal information and medical histories, the following insights were gleaned from the group of 10 elderly participants engaged in the exercise test:

- **Age and Gender Distribution:** The average age of the participants was 67.7 years, with all 10 individuals being female, constituting 100 percent of the group.
- **Living Arrangements:** Among the participants, 30 percent were living independently, 10 percent were residing with a spouse, and 60 percent were part of households with children or grandchildren.
- **Chronic Disease Profile:** All 10 participants reported chronic health conditions, primarily comprising non-communicable diseases (NCDs) commonly observed in the elderly population. These conditions included high blood pressure, blood clots, diabetes, gout, and osteoporosis.
- **Health Checks:** Basic health assessments, including blood pressure measurements, revealed that many participants (9 out of 10) had stable blood pressure levels, posing no hindrance to their participation in the exercise test. However, one participant exhibited elevated blood pressure, warranting caution during the test due to potential risks. Blood oxygen levels and heart rates were within normal ranges for all participants.
- **Medical Clearance:** Following medical evaluation, it was determined that the presence of chronic conditions did not preclude participation in the exercise test for many participants (90 percent). However, one individual experienced dizziness during the test, prompting exclusion from participation due to safety concerns associated with high blood pressure.

Procedure

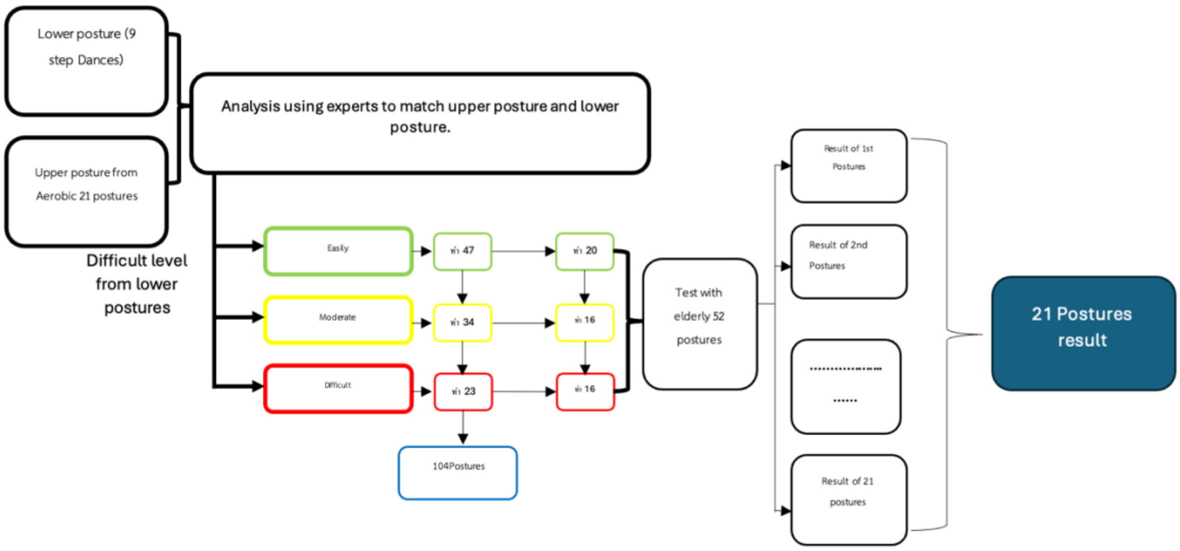


Figure 10: Optimizing Exercise Postures for the Elderly Diagram: An Expert-Led Selection Process

The visual depiction from Figure 10 outlines the systematic methodology employed in the selection of exercise postures, combining 9 lower body postures from the 9-step dance regimen with 13 upper body postures derived from aerobic exercises.

1. **Initiation**: The procedure initiates with a dual-focus on lower body postures from the 9-step dance and upper body postures from aerobic exercises, culminating in 21 distinct postures.
2. **Expert Analysis**: A panel of experts conducts a detailed matching of upper and lower body movements to ensure the resulting exercises are coherent and appropriate for the elderly demographic.
3. **Difficulty Stratification**: The postures are segregated into three difficulty tiers - Easy, Moderate, and Difficult:

    - Of 47 easy postures, 20 are earmarked for subsequent evaluation.
    - Out of 34 moderate postures, 16 are chosen for further testing.
    - Of the 23 difficult postures, 16 are selected for trial.

4. **Aggregate Posture Compilation**: This analysis and selection process results in an aggregate of 104 potential postures.
5. **Elderly Participant Testing**: A subset of these postures, numbering 52, is then empirically tested with elderly participants to ascertain practical viability.
6. **Conclusive Results**: The process culminates with the assimilation of results, where 21 postures are identified as optimally suited for inclusion in the elderly exercise program, reflective of their success in testing.

2.2.8 Edge Computing Development

The prototype system developed is an advancement from the previous system created under the Thai Dance Game Development project, utilizing Edge Computing technology as its core. The collaborative development with CAS Cognizer, a Chinese company, involved the following research steps:

1. **Study of the Previous System:** Understanding the functionalities of the previous system that our research teams developed in the previous Thai Dance Game Development project.
2. **Collaborative Edge Computing System Development:** Collaborative development of the Edge Computing system with CAS Cognizer, focusing on hardware development.
3. **Real User Testing and Hardware Optimization:** Conducting real user tests and optimizing hardware based on user feedback.

The developed system consists of hardware components represented in a block diagram, as shown in Figure 11. The internal components are illustrated in Figure 12, and the interface characteristics, detailing connections to external devices, are depicted in Figure 13.

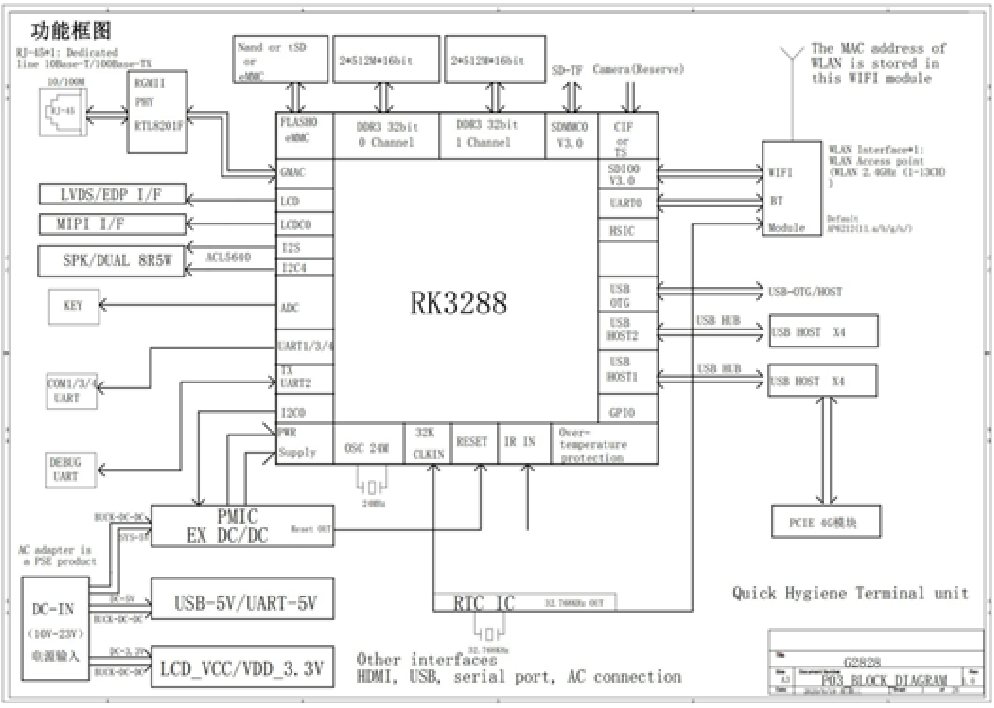


Figure 11: Diagram of the developed Edge Computing system in collaboration with CAS Cognizer, China

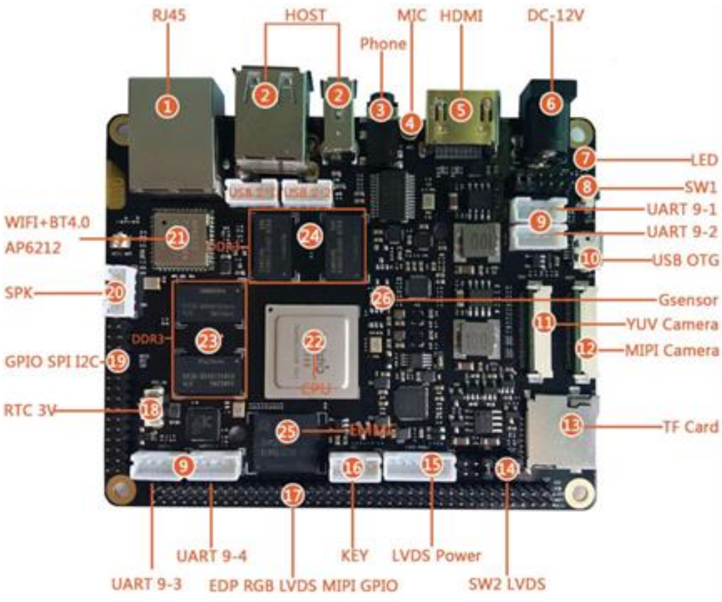


Figure 12: The internal component of the Edge Computing developed

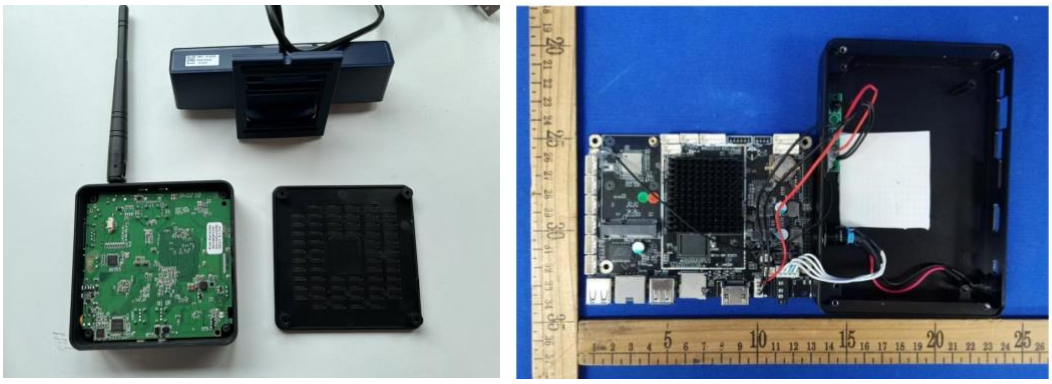


Figure 13: Shown detailing connections to external devices of the Edge Computing system developed in the research project

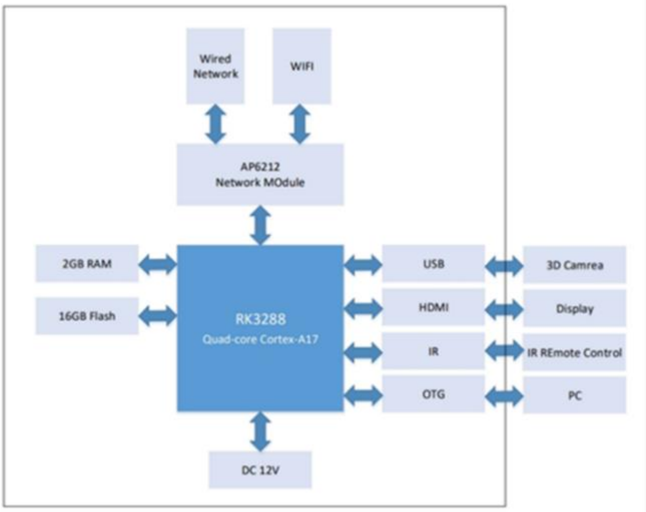


Figure 14: Characteristics of the Interface with external systems in the Edge Computing system

The hardware operation process in the Edge Computing device begins with the CPU, featuring an RK3288 Quad-core Cortex A17 processor. This CPU can process multiple sets of instructions simultaneously, making it suitable for various tasks within Edge Computing, such as motion sensing, process mapping, and accuracy calculations to be displayed on the dashboard.

Following the CPU is the power supply unit, which converts 220V AC to 12V DC using an adapter for device operation. RAM (Random Access Memory) is a vital memory unit that stores data only when powered. GYMBOT's RAM is 2GB, while the Flash Memory unit (EEPROM) has a capacity of 16GB for data storage.

The Network Module, AP6212, facilitates network connectivity, supporting both LAN and Wi-Fi for data exchange between GYMBOT and the Cloud Server. It operates with features like Wi-Fi, Bluetooth 4.0, FM RX, and simultaneous Bluetooth/WLAN receive.

Lastly, the user interface comprises four formats: USB Port for 3D Camera connection, HDMI Port for monitor display, IR for receiving signals from the IR Remote Control, and OTG (USB On the Go) for external device connections such as keyboards, flash drives, or joysticks.

This hardware setup is designed to handle both input and output operations efficiently, providing a comprehensive solution for Edge Computing users.

The developed system is an Edge Computing model that operates as a network close to the data processing source. It works specifically with Motion Data from the 3D Depth Camera, characterized by a considerably large volume of visual and motion data. This approach aims to reduce latency and increase bandwidth for data transmission, addressing speed limitations by minimizing the reliance on cloud processing. The system redistributes processing tasks, minimizing reliance on cloud systems, and shifting processes closer to the data source. The development of this system within the research project seeks to enhance efficiency, particularly to create an impressive experience for users, especially elderly individuals who require a reliable navigation system for exercise.

2.2.9 3D Motion Detection Development

The system's requirements for motion analysis are outlined in Figure 15, emphasizing the necessity of accurate 3D motion detection.

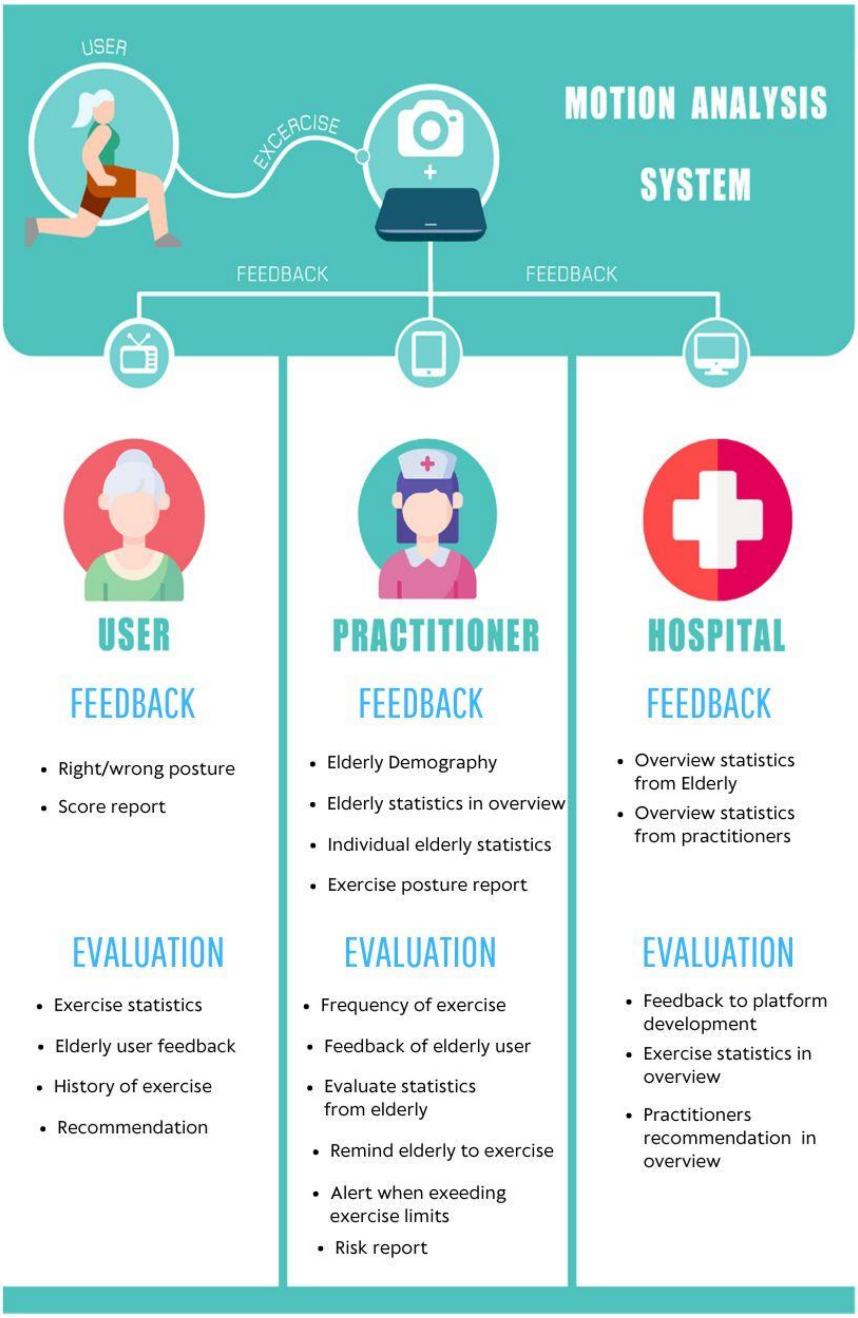


Figure 15: Motion Analysis System Requirements

3D Motion Detection System

The 3D Motion Detection System components are visualized in Figure 16, showcasing the interplay between the Depth Camera sensor, the motion analysis algorithm, and the Animation Controller.

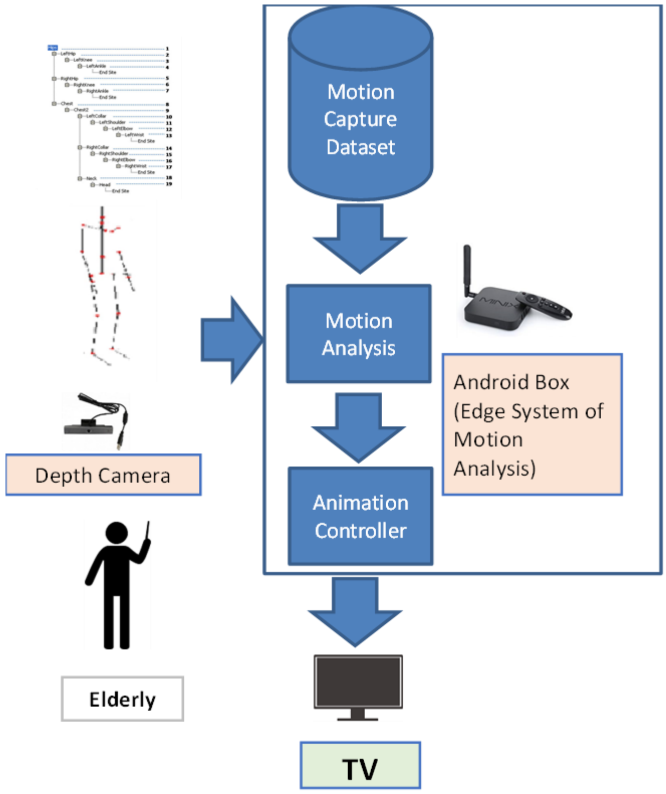


Figure 16: 3D Motion Detection System

Automatic Adjustment Mechanism

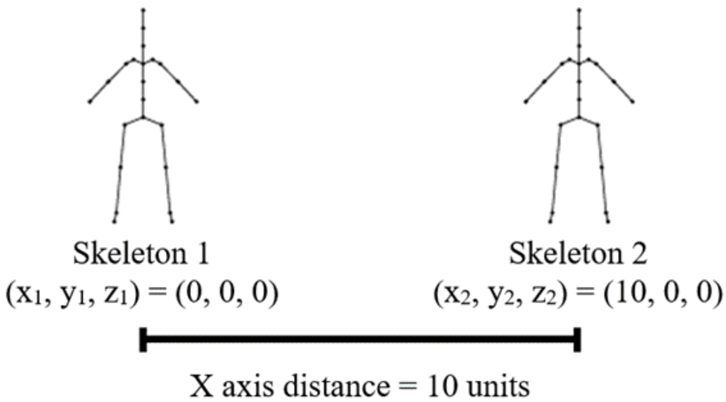


Figure 17: Automatic Adjustment Mechanism

The Two-Method Adjustment mechanism is an essential component of the 3D Human Skeleton Model, particularly when capturing and analyzing motion data of elderly individuals during exercise. The mechanism addresses specific challenges that arise from the limitations of the Depth Camera sensor used in the system.

1. **Motion Data from the Depth Camera**: When the Depth Camera captures the movements of an elderly individual, it generates data on the skeletal structure, transforming physical motion into the 3D Human Skeleton Model. However, errors can arise due to factors like sensor quality, lighting conditions, or distance from the subject. These errors result in inaccuracies in skeletal positions, particularly around the joints and limbs by Dietz et al. (2001)[11].

2. **The Two-Method Adjustment**: To ensure accurate representation of the skeletal movements, the Two-Method Adjustment mechanism applies two distinct corrective methods by Baldissera et al. (1982)[4], Ballesteros et al. (1965)[5], Balter & Zehr (2007)[6]:
    - **Method 1: Data Smoothing**: This method averages out minor deviations in joint and limb positions caused by noise or sensor limitations. It ensures that momentary disruptions in data (like a sudden jerk or misalignment due to depth sensing issues) do not affect the overall model.
    - **Method 2: Joint Realignment**: The second method involves the algorithm actively monitoring the anatomical structure of the human body and correcting any unrealistic positions of bones and joints. For example, if a joint position appears outside the natural range of motion, the algorithm adjusts it to a biologically plausible position based on predefined motion parameters.
3. **Algorithmic Correction**: The system's algorithm automatically compares the captured motion data to a reference model or template of standard human motion. It then adjusts the positions of bones and joints to match the expected movement patterns, correcting any discrepancies caused by the Depth Camera. By using the Two-Method Adjustment, the algorithm continuously refines the skeletal data in real time, ensuring that the generated 3D Human Skeleton Model is both accurate and reliable by Wannier et al. (2001) [35].

The accuracy of the 3D Human Skeleton Model is vital for analysing the physical activities of elderly individuals. Inaccurate data could lead to incorrect conclusions about their mobility, strength, or potential risks for injury by Jung et al. (2020) [18]. Since elderly individuals may have less dynamic movement, any misalignment in joint data or skeletal positioning could distort the analysis significantly. The Two-Method Adjustment mechanism ensures that the model is a faithful representation of their actual movements, enhancing the precision of the monitoring system.

In summary, the Two-Method Adjustment mechanism is crucial because it addresses the errors that can naturally occur during motion capture, refining skeletal data through both smoothing and realignment. This results in a more accurate model, essential for reliable analysis in the context of elderly exercise monitoring.

Software Function Test Report

Table 4 provides a comprehensive Software Function Test Report, outlining the different aspects of the software functionality and ensuring its alignment with the system requirements.

Table 4: Software Function Test Report

NO.	Test Items	Test Case	Test Result
1FT	Gymbot intelligent sports fitness analysis software		
1.1 FT	Login and exit functions		
1.1.1 FT	Login	Login system	PASS
1.1.2 FT	Exit	Exit system	PASS
1.2 FT	My		
1.2.1 FT	Sports archives	Query cumulative exercise days, exercise time, cumulative calorie consumption, and cumulative score	PASS
1.2.2 FT	Calorie analysis	Query the calorie consumption of daily exercise	PASS
1.2.3 FT	Motion time analysis	Query the time of daily exercise	PASS
1.3 FT	Function		
1.3.1 FT	Recommend	Query daily recommended courses	PASS
1.3.2 FT	Training program	Query the training plan made by the software	PASS
1.3.3 FT	Recent training	Query recently trained courses	PASS
1.3.4 FT	Follow	Follow another user	PASS
1.3.4 FT	Online match	Two users can challenge online	PASS
1.3.5 FT	Single mode	Identify and score the body movements of a single person	PASS
1.3.6 FT	Dual mode	Two people identify and score the body movements at the same time	PASS
1.3.7 FT	Invite friends	Invite interested users to challenge	PASS
1.4 FT	Fitness Course		
1.4.1 FT	Various fitness courses	Choose the fitness course	PASS
1.5 FT	Martial art		
1.5.1 FT	Various martial arts courses	Choose martial arts courses	PASS
1.6 FT	Yoga		
1.6.1 FT	Various Yoga courses	Choose yoga courses	PASS

1.7 FT	Dance		
1.7.1 FT	Various dance courses	Choose dance courses	PASS

Motion Analysis Test

Table 5 outlines the results of the motion analysis test, comparing motion detection and 3D image analysis. This table serves to showcase the algorithm's performance in accurately capturing and analyzing motion.

Table 5: Motion Analysis Test Comparison

Test Result	Data	Action type	Total	Effective identification number	Accuracy
	Historical event data	Punch forward with your left and right hands	1000	991	99.1%
		Left hand left fist	1000	996	99.6%
		Right hand right fist	1000	995	99.5%
		Opening and closing jump	1000	992	99.2%
		Left lunge	1000	992	99.2%
		Right lunge	1000	993	99.3%
		Dumbbell shoulder push	1000	996	99.6%
		Side Lateral Raise	1000	997	99.7%
		Standing rotation	1000	984	98.4%
		Bell pot left hand up	1000	995	99.5%
		Bell pot right hand up	1000	996	99.6%
		Squat	1000	998	99.8%

		V-Ring	1000	998	99.8%
		High leg lift	1000	991	99.1%
		One hand opening and closing	1000	993	99.3%
		Ski jump	1000	994	99.4%
	Average motion extraction speed		82 ms		
	Average action ratio speed		10 ms		

Platform Architecture

Figure 18 illustrates the architecture of the exercise analysis platform for elderly individuals, emphasizing the integration of the Depth Camera sensor and motion analysis algorithm.

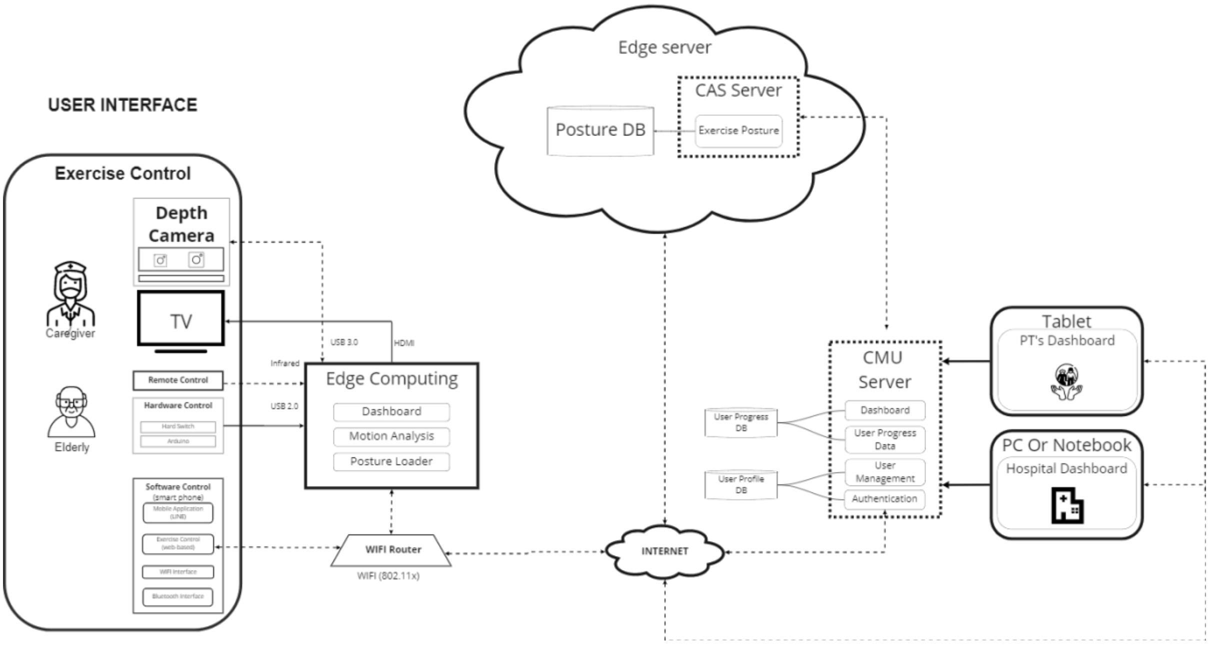


Figure 18: Platform Architecture for Exercise Analysis

Platform Operation

This segment orchestrates the seamless operation of the platform, ensuring effective communication with elderly users and facilitating their engagement in tailored exercise routines. Caregivers or assistants initially guide and instruct elderly users through the following components:

- **Depth Camera:** Records motion during exercises.
- **TV:** Displays information to elderly users.
- **Remote Control:** Controls Edge Computing system functions, recording exercise data, and importing standardized motions from the Cloud system.
- **Hardware Control:** Likely experimental, exploring user-friendly interfaces (e.g., foot pedals or UX/UI systems).

- **Software Control:** A mobile system designed to control motion analysis tools and potentially evolve the platform in the future.

Edge Server: This component serves as the repository for a standardized exercise motion database. It transmits this data to the Edge Computing system via the Internet for accurate exercise recognition and in-depth analysis.

Edge Computing: Utilizes an Android Box for data storage and analysis. It collects user data for future trend analysis, encompassing exercise correctness, abnormalities, and user progress.

CMU Server: Stores preliminary data, processes information from Edge Computing, and communicates with user dashboards for caretakers and healthcare personnel.

Caretaker Dashboard: Monitors elderly users' exercise progress and provides information to caretakers, such as nurses or physical therapists.

Healthcare Facility Dashboard: Displays exercise data, user issues, and caretaker activities, enabling healthcare facilities to adjust policies or systems for sustainable use.

Video Records of Exercise Posture

In this section, we detail the process of recording exercise postures for elderly individuals using Motion Capture technology. These video clips are a crucial component of the project, as they will be uploaded to the cloud and accessed by the edge system. The posture videos will then be used to guide elderly users through exercise routines, ensuring consistency and accuracy in their exercise sessions. This approach allows for remote access and effective exercise instruction tailored to the elderly.

Operation Method

1. Coordinate with the dance performer group for exercise posture recording.
2. Coordinate with the recording team to plan and storyboard the exercise posture recording.
3. Conduct a meeting with dance performers and the recording team to explain the recording process for smooth execution on the actual recording day.
4. Reserve a room for recording exercise postures.
5. Record exercise postures for the elderly using Motion Capture technology.
6. Edit the recorded clips according to the set postures defined by the dance instructor, totaling 3 sets.

Figure 19: Exercise Posture Video Recording

Research Summary

Exercise postures were successfully recorded using Motion Capture technology. The recorded video clips will be used in the project and the elderly exercise equipment. The next steps involve consulting with the research team to select background music, as well as combining each posture to create a set that meets the standard for elderly exercise.

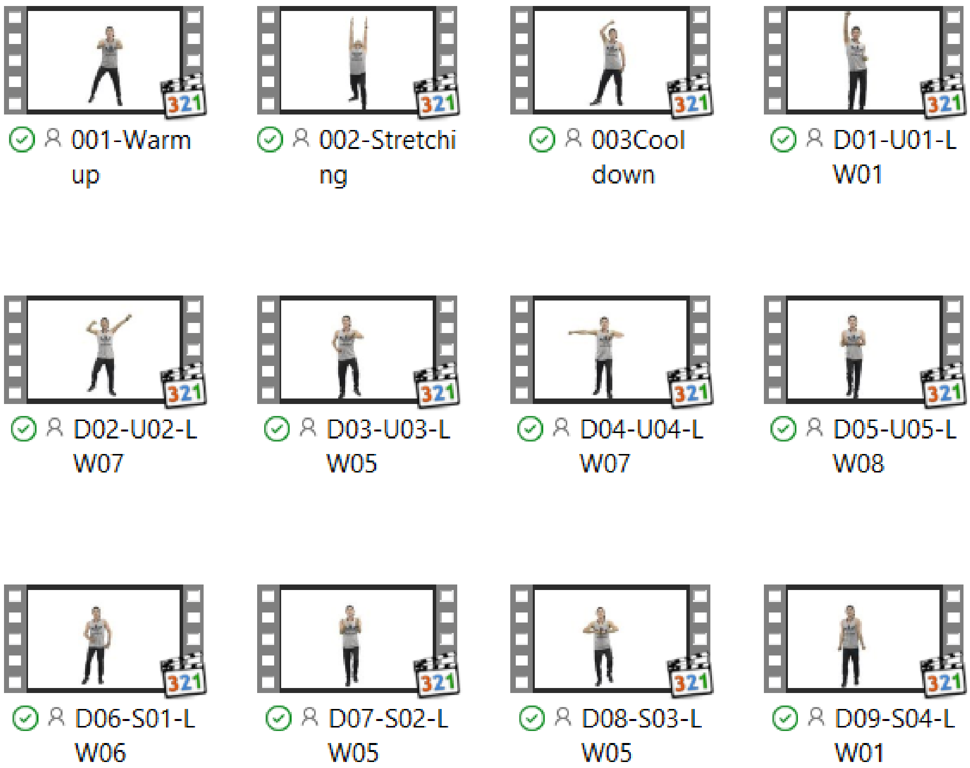


Figure 20: Exercise Posture Video Clip

After editing, a total of 21 clips with 21 postures, maintaining a pace of 100 Bpm, were obtained. The Dance Matrix table below illustrates the selected postures for exercise posture video recording.

136-200 Beat/Min	✶/❖	✶/❖	✶/❖
91-135 Beat/Min	✶/❖	✶/❖	✶/❖
40-90 Beat/Min	✶/❖	✶/❖	✶/❖
	5 Minute	**10 Minute**	**15 Minute**

Figure 21: Dance Matrix Table for Exercise Posture Recording

After editing, five video clips were produced for use in the exercise equipment:

- Exercise Set 04 (accompanying Elderly Song 1)
- Exercise Set 05 (accompanying Elderly Song 2)
- Exercise Set 06 (accompanying Elderly Song 3)
- Warm-up + Stretching (non-copyrighted music)
- Stretching + Cool down (non-copyrighted music)

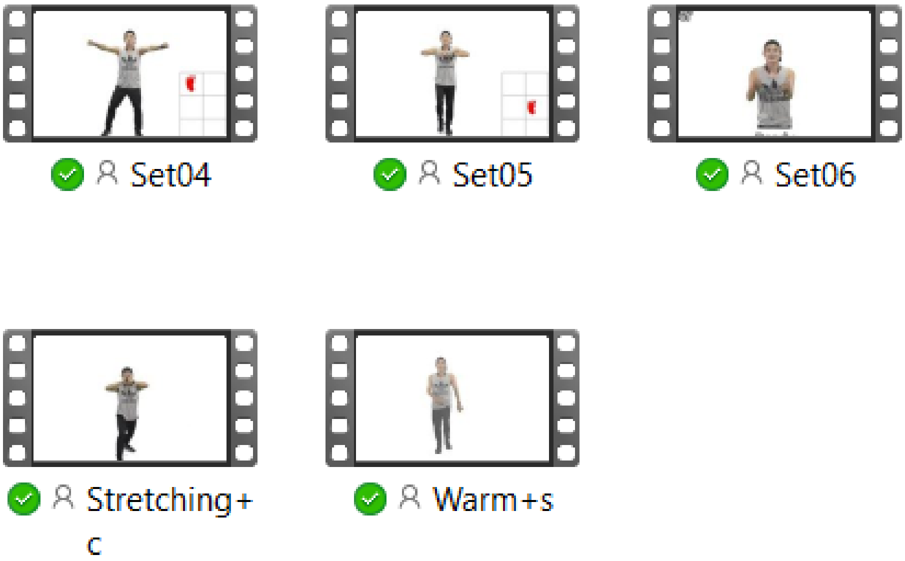


Figure 22: Video clips integrated into the exercise equipment

The next session could focus on Integration and Testing of the recorded video clips in the exercise equipment system. This would involve detailing how the clips are uploaded to the cloud, then will be accessed by the edge system, and used in real-time during elderly exercise routines. It could also cover any testing or feedback gathered during the implementation phase.

2.2.10 Monitoring System Development

2.2.10.1 Principles of Exercise Plan

To enhance elderly care through the designed system, it is imperative to meticulously monitor exercise data at various stages by Kao & Ferris (2005) [21]. The monitoring system is strategically developed to align with the FITT principles, encompassing Frequency, Intensity, Time, and Type of exercise.

1. **Frequency (F):** Frequency refers to how often elderly individuals engage in exercise. The monitoring system diligently captures and analyzes data on the regularity and consistency of exercise routines. This insight aids in understanding the exercise habits of elderly users over time.
2. **Intensity (I):** Intensity, a crucial aspect of effective exercise, is monitored using smartwatches. These devices collect real-time data such as heart rate and exertion levels, providing valuable information on the intensity of physical activities. This data assists in tailoring exercise recommendations based on the individual's capabilities.

3. **Time (T):** The duration of exercise sessions, a key parameter for assessing the effectiveness of physical activities, is tracked by the monitoring system. By analyzing the time spent on various exercises, the system ensures that elderly users meet recommended thresholds for different types of activities, contributing to their overall well-being.
4. **Type (T):** The Motion Analysis Exercise Edge system, selected by users for exercise guidance, plays a pivotal role in providing information on the type of exercises performed. This includes details about specific muscle groups targeted during each exercise. The system utilizes this information to offer tailored feedback and insights, promoting diversity and effectiveness in the exercise routine by Dietz (2002) [10].

This comprehensive approach to monitoring, incorporating the FITT principles, enables the system to provide a holistic understanding of elderly users' exercise behaviors. By leveraging data from both the Edge Computing unit and smartwatches, the monitoring system contributes to personalized and effective elderly care. The insights derived from this monitoring process empower caregivers and healthcare professionals to make informed decisions and adjustments to further optimize the well-being of elderly individuals.

The development of the Monitoring System, intricately designed to capture and analyze exercise data under the FITT principles, marks a significant advancement in elderly care technology. By systematically recording the Frequency, Intensity, Time, and Type of exercises, we have laid a robust foundation for a data-driven approach to maintaining and enhancing the health of older adults.

As we transition from the meticulous development of this Monitoring System to its practical application, we embark on the next phase: the integration of this system with our Motion Analysis System. This integration is poised to bring forth a seamless user experience, where real-time data flow enables instant feedback and adaptive recommendations.

In the upcoming session “Integration of Smartwatch Data with FITT Dashboard” we will delve into the architectural developments that facilitate this integration. The culmination of these efforts is a user-friendly dashboard that not only displays vital exercise data in an accessible manner but also embodies the FITT principles in its design and functionality. This dashboard serves as the nexus of our monitoring efforts, offering a comprehensive view of each participant's exercise journey, and enabling caregivers and healthcare professionals to fine-tune exercise programs to the unique needs of each elderly individual.

2.2.10.2 Collaborative Effort: CMU and Northumbria University

The collaborative effort between Chiang Mai University. (CMU) and Northumbria University (NU) has resulted in the successful development of a smartwatch system with advanced health monitoring capabilities. The project emphasizes accuracy, real-time data provision, and flexibility in data storage.

Hardware Components

1. **ESP32 Microcontroller:**
    - Low-cost, low-power system-on-a-chip with Wi-Fi and Bluetooth capabilities.
    - Central to the smartwatch's processing capabilities.
2. **Sensors:**
    - **Heart Rate Sensor:**
        - Accurately detects the user's heart rate.
    - **Accelerometer Sensor:**

    - Measures user movement through acceleration.

  - Rigorous testing ensures proper functionality before integration into the final system.

Software Development

1. **Firmware Development:**
    - Developed using Arduino IDE for ESP32.
    - Lilygo libraries used for seamless sensor interfacing.
    - Various libraries (Wire.h, MAX30105.h, BluetoothSerial.h, etc.) are employed for communication, data parsing, and management.
2. **Task Management:**
    - TaskScheduler.h utilized for managing periodic tasks, ensuring efficient system operation.

Functionality

1. **Health Monitoring:**
    - System designed to accurately track heart rate and activity levels.
    - Flexible data transmission options - via Bluetooth or Wi-Fi to a mobile app or a backend server.
2. **Mobile App and Backend Server:**
    - **Mobile App Development:**
        - Flutter framework used for mobile app development.
        - Real-time data display allows users to choose between local storage or backend server transmission.
    - **Backend Server Development:**
        - Laravel/PHP framework employed for the backend server.
        - Admin app developed for data monitoring and analytics.
        - Firebase is used for cloud storage.
        - Laravel API handles requests from both the mobile app and the smartwatch.

Conclusion and Results

1. **Successful Data Collection:**
    - Smartwatch effectively collects and transmits data to both the mobile app and the backend server.
    - Real-time data viewing is available on the mobile app.
2. **Backend Server Functionality:**
    - Serves as an edge server, facilitating preprocessing of data before storage in the Firebase database.

3. **Accuracy and Performance Testing:**

    - System rigorously tested, achieving +/- 5 beats per minute accuracy for heart rate readings.
    - Scalable design for future functionalities.

Key Features

- Accurate heart rate measurement.
- Real-time data viewing on the mobile app.
- Flexible data storage options (local or cloud).
- Scalable system for future functionalities.

The collaborative smartwatch project between CMU and NU has successfully delivered a comprehensive health monitoring system. With accurate measurements, real-time data provision, and flexibility in data storage, the smartwatch, mobile app, and backend server collectively provide users with a seamless and efficient health-tracking experience. The project sets the foundation for further advancements and integrations in wearable health technology.

2.2.10.3 Integration of Smartwatch Data with FITT Dashboard

The smartwatch project progresses with the integration of heart rate data into a Node.js dashboard using Firebase and MongoDB. The system ensures real-time updates and seamless data flow, offering elderly users a dynamic visualization of exercise intensity based on FITT principles (Frequency, Intensity, Time, Type).

- **Firebase Interaction:** Smartwatch reports heart rate to Firebase Cloud Server in real-time.
- **Data Processing:** The backend fetches data from Firebase and transfers it to MongoDB for further analysis.
- **Node.js Dashboard:** Dynamically visualizes heart rate data, categorizing exercise based on FITT principles.
- **FITT Principal Focus:** Frequency, Intensity, Time, and Type guide exercise assessment for elderly users.
- **Dynamic Visualization:** Node.js dashboard updates in real-time, allowing users to monitor exercise intensity.
- **Reporting and Analytics:** The system generates concise reports on exercise patterns and adherence to FITT principles.
- **Key Features:**
    - Seamless data flow from smartwatch to Firebase to MongoDB.
    - Real-time Node.js dashboard for exercise intensity monitoring.
    - FITT principles are used for comprehensive exercise assessment.

The integration of smartwatch data into the Node.js dashboard provides a streamlined solution for real-time health monitoring. By applying FITT principles, the system aims to offer valuable insights into elderly exercise routines, fostering engagement, encouraging healthy habits, and contributing to overall well-being by Choi et al. (2013)[8].

2.2.10.4 Participating Health care practitioners

Project Planning and Design

Physical Therapist (Doctor): Collaborates in the initial planning phase, offering insights into health parameters and exercise considerations for the elderly. Shapes the overall project objectives to align with healthcare standards.

Smartwatch Development

Physical Exercise Experts: Contribute to the design of exercise algorithms and parameters embedded in the smartwatch. Ensure that the technology aligns with safe and effective exercise practices for elderly users.

Integration with Node.js Dashboard

Physical Exercise Experts: Provide input on how exercise intensity data can be accurately interpreted and visualized on the Node.js dashboard. Ensures the dashboard reflects meaningful exercise assessments based on FITT principles.

Collaboration with Healthcare Practitioners

Physical Therapist (Doctor): Actively collaborates with the team during the integration phase, ensuring that the smartwatch data aligns with health monitoring standards and contributes to effective elderly care.

Participating in Experiments and Assessments

Caregivers: Engage in the design of experiments and assessments. Their insights into the daily challenges and routines of the elderly population guide the project's practical implementation.

Analysis of Knowledge Sharing

Physical Therapists (Doctors) and Physical Exercise Experts: Play a key role in analyzing knowledge-sharing strategies. Evaluate the effectiveness of communication channels and materials used for educating elderly participants.

Dashboard Utilization and User Feedback

Caregivers: Act as a bridge between the technological solution and end-users. Provide feedback on the usability of the Node.js dashboard and contribute to refining the user interface for elderly individuals.

Continuous Improvement

All Practitioners: Collaborate in an ongoing manner, contributing insights for continuous improvement. The physical therapist, exercise experts, and caregivers collectively adapt strategies based on emerging challenges and participant feedback by Zehr & Duysens (2004)[38].

In summary, the project embraces a multi-disciplinary approach, leveraging the expertise of physical therapists (doctors), physical exercise experts, and caregivers at various stages. This ensures the development of a comprehensive, effective, and user-friendly smartwatch health monitoring system for the elderly.

2.2.10.5 Training requirements and plan

Training Requirements

Before embarking on the research project, it is crucial to identify the training requirements necessary to ensure the successful execution of the study. The following training requirements have been identified:

1. **Technical Training:** To operate and manage the technology and equipment involved in the study, including the GymBot 3D depth cameras, LilyGo wearable devices, and the dashboard system.
2. **Ethical Research Training:** Ensuring that all research personnel are well-versed in ethical guidelines and regulations related to human research, informed consent, and participant confidentiality.
3. **Data Collection Training:** Equipping research staff with the knowledge and skills required for collecting accurate and relevant data from elderly participants, as well as ensuring their safety during exercise sessions.
4. **Dashboard Usage Training:** Training the specialists who will use the dashboard system to monitor the exercise data and progress of the elderly participants.

Training Plan

To address the identified training requirements, the following plan has been developed:

1. **Technical Training:**
    - All research staff involved in the project will undergo technical training sessions led by experts in the field. This training will cover the operation and maintenance of the GymBot 3D depth cameras, LilyGo wearable devices, and related equipment.
    - The training will include practical demonstrations, hands-on exercises, and troubleshooting scenarios to ensure staff proficiency.
2. **Ethical Research Training:**
    - Research personnel will receive comprehensive training in ethical research practices, including obtaining informed consent, protecting participant privacy, and adhering to relevant regulations.
    - This training will be provided by experts in research ethics and will be mandatory for all team members.
3. **Data Collection Training:**
    - Those responsible for data collection from elderly participants will undergo specialized training to ensure accurate and consistent data collection.
    - Training will encompass proper data recording techniques, participant interaction, and emergency response procedures in case of adverse events.
4. **Dashboard Usage Training:**
    - The three specialists physical exercise or sports scientists who will utilize the dashboard system will receive extensive training on its functionality and usage.
    - Training sessions will include hands-on practice with the dashboard, real-time monitoring, and data interpretation.

2.2.10.6 Data Storage and Visualization

Data Storage

MongoDB serves as the primary database for storing user and activity data, supporting various API interactions such as user authentication, login, course listings, and extracting summary information. It facilitates seamless communication between the GYMBOT platform and the MongoDB database. The integration involves exchanging data using requests and responses in JSON format, ensuring compatibility with both GYMBOT's Chinese API and the APIs available. Developed locally, the MongoDB database stores and manages a wide range of data related to user profiles, course details and statistical summary information efficiently. This contributes to the functioning and efficiency of the GYMBOT service.

Data Structure

The data structure is designed to handle input from multiple sources according to the requirements for storing data based on the FITT principles. It integrates data from the edge system, which captures information such as frequency, time, and muscle specifications. Additionally, intensity data is collected and calculated from a smartwatch, while demographic information about the elderly, along with other necessary data, is included for comprehensive monitoring. This data structure also incorporates inputs from practitioners, enabling detailed tracking and analysis of exercise behavior in elderly individuals. This multi-source approach ensures efficient and accurate data handling for monitoring and improving elderly exercise routines.

Edge Terminal

The prototype system, building on the original Thai Dance Game Development Project, leverages Edge Computing as the core technology, developed in collaboration with CAS Cognizer Company, China. The system is designed to reduce latency and enhance bandwidth for handling large volumes of motion data. Instead of relying heavily on cloud processing, Edge Computing brings data processing closer to the source, significantly improving performance and user experience, especially for elderly users engaging in exercise.

In this section, we focus on the benefits of Edge Computing in terms of data storage and visualization. By processing motion data locally at the edge, it reduces the burden on cloud systems, allowing for faster data transmission and real-time feedback. This is critical for efficient visualization of exercise routines and storing large amounts of user-generated data, making the system more responsive and scalable.

2.2.10.7 System API and Mobile Web Application Integration

Introduction

For pilot case II, we aim to design a comprehensive, real-time exercise monitoring and analysis platform for elderly participants. It integrates the LilyGo smartwatch, motion analysis systems, and a cloud-based architecture through robust API development. The goal is to support elderly users in maintaining and improving their physical health using structured exercise routines based on the FITT (Frequency, Intensity, Time, Type) principle.

This report outlines the API development and the integration of the mobile web application with the GYMBOT motion analysis system, along with the seamless transmission of real-time data to Firebase and MongoDB databases. The project enables both users and caregivers to track exercise progress in an intuitive, data-driven manner.

Overview of API Functions

The API (Application Programming Interface) serves as the central communication layer for transmitting data between the GYMBOT system, the LilyGo smartwatch, and the cloud infrastructure (Firebase, MongoDB). The APIs ensure real-time data flow in JSON format, enabling efficient and secure data management by Allaire et al. (2013)[2].

Edge system Key API functions include:

1. Verify & Register: Sends verification emails to the user's address through the GYMBOT API located in China. After verifying the code, the user registration process is completed by sending the details back to the Chinese API.
2. Login: User credentials are sent to the GYMBOT API for authentication, and upon successful login, the credentials are stored in the database.
3. Course List: Retrieves available course data from the GYMBOT API for display on the user's dashboard.
4. Connect to GYMBOT: Initiates a start command through the API to connect the user with the GYMBOT system for their workout sessions.
5. Start Course: A command is sent via the API to start the user's course, with the data transmitted to both the GYMBOT API and the local database.
6. Retrieve User Summary: The user's exercise summary data is pulled from the GYMBOT API and stored in the local database for reporting purposes.
7. Update Profile Information: The user's profile data is fetched from the GYMBOT API, updated locally, and then synchronized with the GYMBOT system.
8. Change Password: Fires a command to the GYMBOT API to update the user's password in real time.

Mobile Web Application Integration

The Mobile Web Application provides elderly participants with a simple and accessible interface to manage their exercise programs. The application is fully integrated with the GYMBOT system through APIs, offering real-time data synchronization.

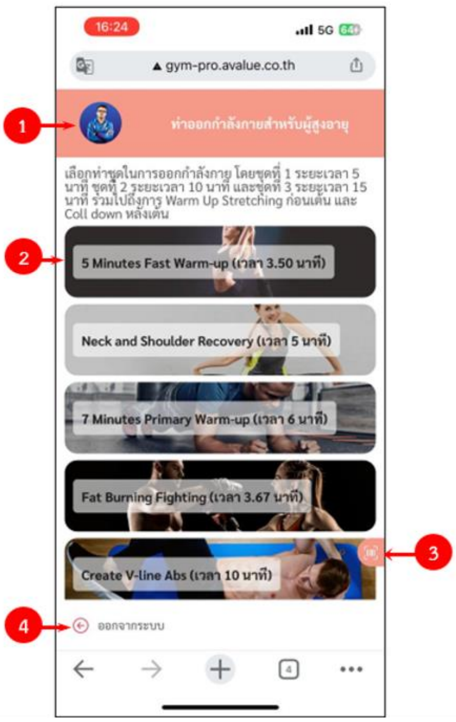


Figure 23: First Page of the Mobile Web Application

This screen shows the user's profile, available course items, a QR code scanning option, and a logout button. The mobile application includes a QR code scanning feature that allows users to synchronize their profiles with the GYMBOT motion analysis system. The QR code is displayed on a TV screen connected to the GYMBOT Pro Box.

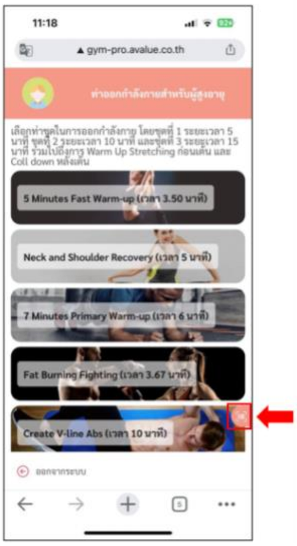


Figure 24: QR Code Scan for Synchronization with GYMBOT System

The interface prompts users to scan the QR code displayed on their TV to synchronize their mobile device with the motion analysis system.

Figure 25: QR Code Scanning Process in Motion Analysis System

The application scans the QR code, establishing a connection between the user’s profile and the motion analysis system.

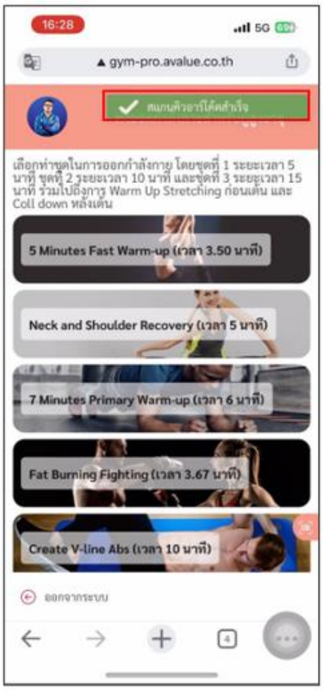


Figure 26: Successful QR Code Scan Confirmation

Once the scan is successful, a confirmation message is displayed, and the user is redirected to their exercise program dashboard.

Smartwatch and Firebase Integration

The LilyGo smartwatch captures health metrics such as heart rate and physical activity, which are transmitted via an API to Firebase. This integration allows for real-time monitoring and feedback.

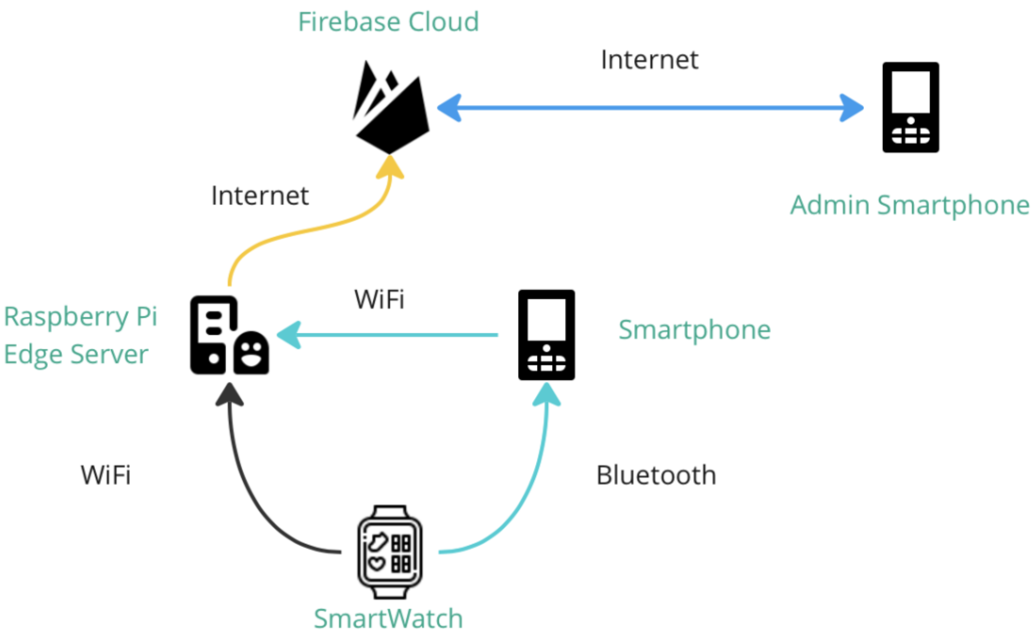


Figure 27: Smartwatch and Firebase Integration Architecture

This diagram demonstrates the data flow from the smartwatch to Firebase, where metrics like heart rate are stored for real-time analysis.

Integration with Motion Analysis System

The heart rate data from the smartwatch is integrated with the GYMBOT motion analysis system, where it is merged with exercise routine data and displayed on the user dashboard according to the FITT principle.

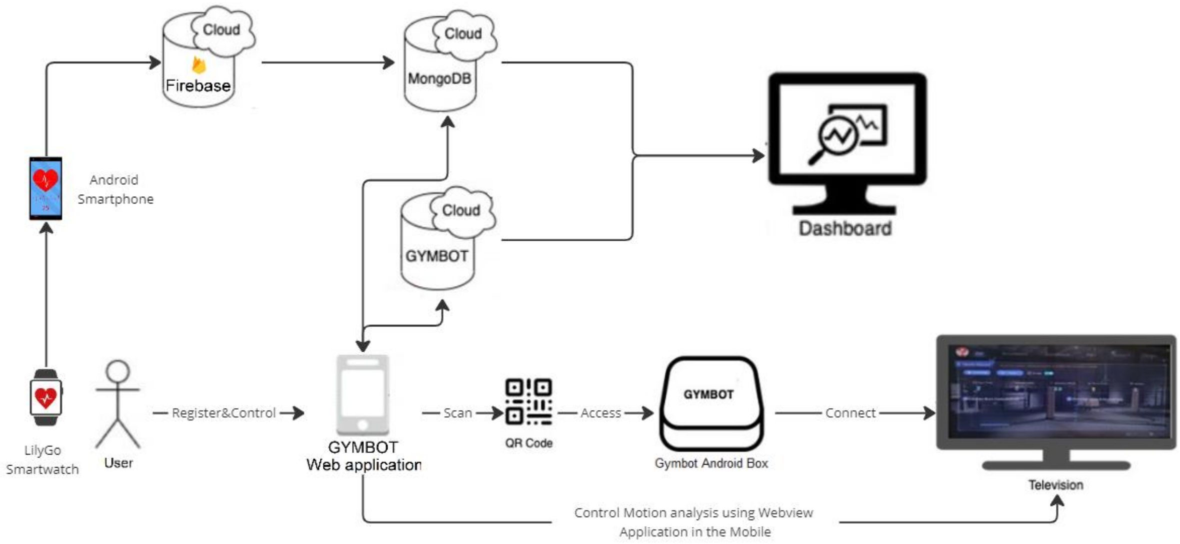


Figure 28: System Integration and Dashboard Display Flowchart

The flowchart outlines how data from the smartwatch and the GYMBOT system are processed and displayed on the dashboard for real-time feedback.

2.2.10.8 Data Management and Visualization

Cloud-Based Data Architecture

The project uses MongoDB for cloud-based data storage, which allows for flexible and scalable data management. APIs ensure the secure transmission of data between the cloud and the client-side applications.

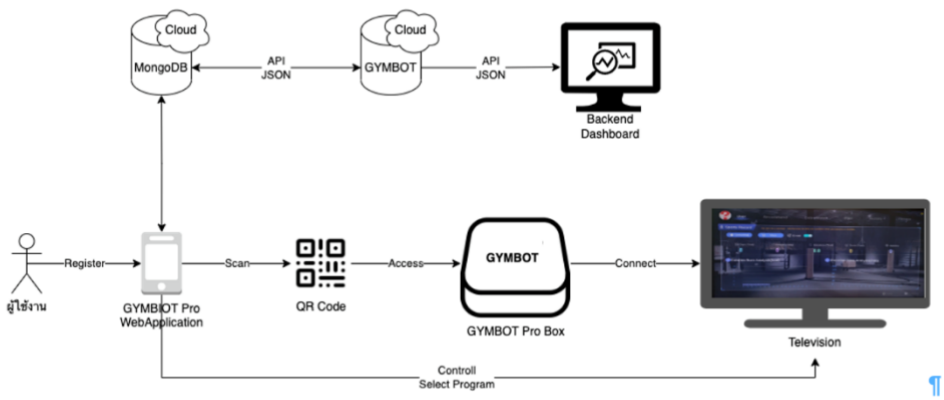
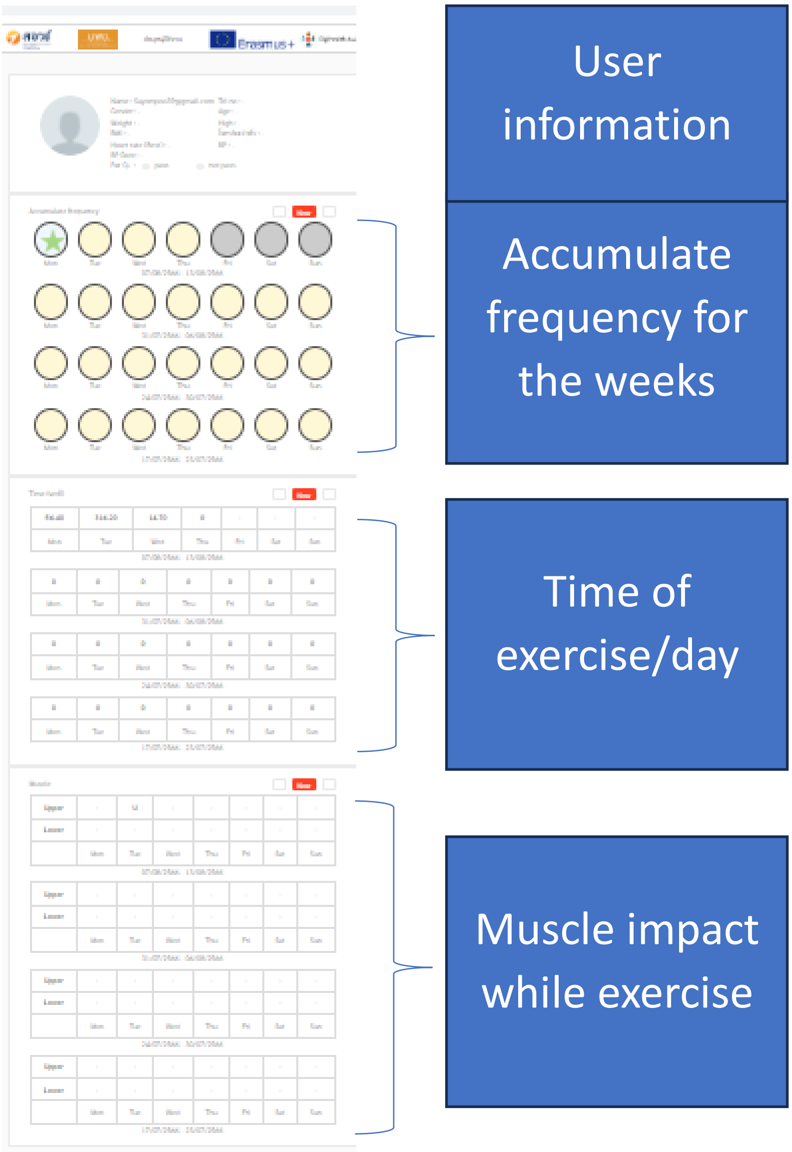


Figure 29: Cloud-Based Data Architecture in the GYMBOT System

This architecture illustrates how data is stored and managed in MongoDB, with APIs facilitating real-time data exchange.



The dashboard provides both users and caregivers with a comprehensive view of exercise progress and health metrics. The data is visualized through graphs and reports based on the FITT principle. The dashboard provides users with a clear view of their exercise progress, including achievements and exercise goals based on the FITT principle.

2.2.10.9 Posture Dataset and Motion Analysis

The system uses a cloud-based posture dataset to compare real-time movement data captured by the motion analysis system against pre-recorded postures stored in the cloud. This ensures that exercises are performed correctly, and any deviations are identified.

Figure 30: Dashboard Layout for Visualizing Health and Exercise Data

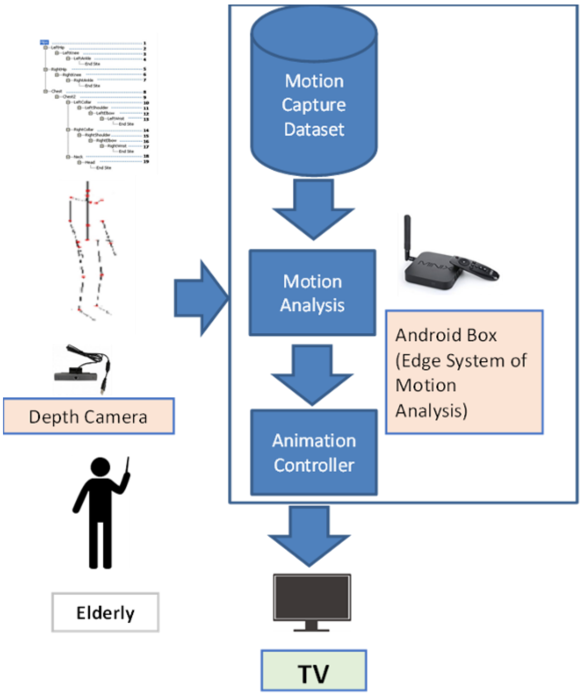


Figure 31: 3D Motion Detection System with Cloud-Based Posture Dataset

The figure shows how the cloud-stored dataset is accessed during real-time exercise sessions to compare and analyze user movements.

2.2.11 Dataset Collection and Analysis

2.2.11.1 Data Collection Plan

In the DigiHealth project, data collection serves as a critical element in monitoring and enhancing the exercise routines of elderly participants. The process entails systematically gathering detailed exercise metrics under the FITT principle (Frequency, Intensity, Time, and Type) for each session. This phase encompasses the training of practitioners in the effective use of the dashboard for data tracking and analysis, followed by the implementation of exercise trials with elderly participants. During these trials, data is collected and transmitted to a centralized dashboard, which offers a visual interface for real-time monitoring and evaluation. The collected data is subsequently utilized for further visualization and analysis, facilitating the continuous monitoring of participants' performance, ensuring the safety and effectiveness of the intervention, and allowing for timely adjustments to optimize health outcomes for the elderly population.

Elderly Participants Selection

Twenty elderly participants were selected for the study based on specific inclusion criteria to ensure the reliability and safety of the exercise monitoring system. The criteria were as follows:

1. Age: Participants had to be 60 years or older to focus on the elderly population.

2. Health Status: Participants with no history of injuries or diseases that could influence balance function were chosen to avoid any confounding factors related to health issues.

3. Alcohol Consumption: Participants were required to abstain from alcohol consumption for at least 12 hours before the experiment to ensure that their balance and physical capabilities were not impaired.

4. Screening Test: Participants needed to pass the Par-Q+ (Physical Activity Readiness Questionnaire) test administered by a physical therapist. The Par-Q+ test included questions on

heart conditions, chest pain, dizziness, bone/joint problems, and medication use, requiring a "no" answer to all questions to pass. Only those who scored 7 out of 7 on the test, indicating full readiness for physical activity, were included in the study.

Participants were recruited through the Fa-Ham Elderly Group. Information sessions were held at these locations to inform potential participants about the study's objectives, procedures, and eligibility criteria. Interested individuals were invited to attend a screening session where they underwent the Par-Q+ test and were evaluated based on the inclusion criteria. The result of the selection of elderly participants is in Table 6 below

During the recruitment sessions, researchers provided detailed explanations of the study to ensure that potential participants fully understood the commitment and activities involved. This transparent communication helped to build trust and ensure that participants were genuinely interested in contributing to the research without any external incentives.

No incentives were provided for participation in this study. The focus was on voluntary participation to ensure that individuals were motivated by a genuine interest in the research and its potential benefits for elderly care. By not offering incentives, the study aimed to avoid any undue influence on participants' decision to join, thus maintaining the ethical standards of voluntary participation.

These recruitment methods, coupled with the stringent selection criteria, helped ensure that the participants were both willing and able to engage safely and effectively in the exercise regimens being tested.

Table 6: Demography of participants

User	Age	Heart Rate	Blood Pressure	Sex	Weight (kg)	Height (cm)	BMI	Health Status
User1	66	91	104/67	Female	56	155	23.31	Normal
User2	60	64	112/76	Female	47	158	18.83	Underweight
User3	62	69	136/84	Male	57	163	21.45	Normal
User4	60	87	141/83	Female	60	155	24.97	Overweight
User5	71	76	134/87	Female	59	154	24.88	Overweight
User6	70	73	138/78	Female	50	150	22.22	Normal
User7	69	82	121/73	Female	60	162	22.86	Normal
User8	65	82	118/78	Female	67	165	24.61	Overweight
User9	65	75	140/80	Female	55	154	23.19	Normal
User10	67	91	142/75	Female	62	156	25.48	Overweight
User11	62	72	137/81	Female	58	162	22.10	Normal
User12	61	74	128/83	Female	54	161	20.83	Normal
User13	64	68	134/81	Male	47	155	19.56	Underweight
User14	63	65	132/85	Female	52	153	22.21	Normal
User15	70	88	138/85	Female	68	151	29.82	Overweight
User16	72	93	135/89	Female	65	157	26.37	Overweight
User17	67	89	137/85	Female	51	165	18.73	Underweight
User18	69	91	143/87	Female	49	153	20.93	Normal
User19	73	82	139/91	Female	62	168	21.97	Normal
User20	65	73	142/87	Female	57	157	23.12	Normal

Expert Participants Selection

Experts were approached through professional networks, academic institutions, and elderly care organizations. The selection process involved the following steps:

1. **Identification:** Potential experts were identified based on their professional backgrounds and experience with elderly care. This included contacting professional associations, academic departments, and care facilities.
2. **Invitation:** Identified experts were invited to participate in the study through formal invitations, which included detailed information about the study's objectives, the role of the experts, and the expected time commitment.

3. **Screening:** Interested experts underwent a screening process to confirm their qualifications and experience. This involved reviewing their professional credentials, work history, and specific expertise related to elderly care.
4. **Confirmation:** Selected experts received confirmation of their participation, along with further details about the study protocols and their specific roles within the research.

Following the methodology employed by Boyette et al. (2001) [16], the selection method for these expert participants was designed to ensure effective participation and a high level of expertise, thereby enhancing the validity and applicability of the research. The physical therapists contributed expertise in areas such as sports injury prevention, geriatric physical therapy, and general physical therapy. The sports scientists provided knowledge in exercise design for both athletes and elderly individuals, while the caregivers offered valuable insights from their backgrounds in education, social sciences, and accounting. This multidisciplinary team approach facilitated a comprehensive strategy to address the exercise needs of elderly populations. The result of practitioner selection will be shown in Table 7 below.

Table 7: The demographic details of practitioners

Profession	Age	Experience	Gender	Location	Education	Expertise	Working with Elderly
Physical Therapist	26	3 years	Male	Chiang Mai	Physical Therapy	Sports injury prevention and treatment	Yes
Physical Therapist	26	3 years	Female	Chiang Mai	Physical Therapy	Geriatric physical therapy	Yes
Physical Therapist	30	More than 3 years	Male	Chiang Mai	Physical Therapy	General physical therapy	Yes
Sports Scientist	30	More than 3 years	Male	Chiang Mai	Education, Sports Science	Exercise design for athletes	Yes
Sports Scientist	41	More than 3 years	Male	Chiang Mai	Education, Sports Science	Exercise design for the elderly	Yes
Sports Scientist	44	More than 3 years	Male	Chiang Mai	Education, Sports Science	General exercise design and workout routines	Yes
Care Giver	55	3 years	Female	Chiang Mai	Education	Teaching mathematics and science	Yes
Care Giver	61	More than 3 years	Female	Chiang Mai	Social Sciences	Social and human resource management	Yes
Care Giver	57	2 years	Female	Chiang Mai	Accounting	General Accounting	Yes

The study received approval from the Chiang Mai University Research Ethics Committee. The process of obtaining ethics approval involved submitting a detailed research proposal outlining the study's objectives, methodology, potential risks, and benefits to the participants. The ethics committee reviewed the proposal to ensure that the study adhered to ethical standards, particularly regarding the safety and well-being of participants.

Informed consent was obtained from all participants before their inclusion in the study. This involved providing participants with comprehensive information about the study, including its purpose, procedures, potential risks, and benefits. Participants were allowed to ask questions and were required to sign a consent form indicating their voluntary agreement to participate.

The research team ensured effective communication through various channels, including telephone, email, mail, and in-person meetings and workshops. This collaborative effort was essential in achieving the study's objectives and integrating diverse expertise into the research. By maintaining transparent and open communication, the team was able to address any concerns and ensure that participants were well-informed and comfortable with their involvement in the study.

2.2.11.2 Data Collection Procedure

Procedure for Practitioners

Creating an orientation for dashboard usage and designing activities to test its functionality are critical steps in evaluating both its performance and user experience. The process begins with practitioners reading the user manual to familiarize themselves with the dashboard's features and navigation. This foundational step ensures that they are well-prepared to effectively use and evaluate the system.

Following the orientation, practitioners engage in a series of tasks designed to test various aspects of the dashboard. These tasks include viewing user details, examining comprehensive reports, and analyzing FITT (Frequency, Intensity, Time, and Type) data to assess clarity and usability. Practitioners also practice recording and updating user information to test data management processes.

After completing these tasks, practitioners fill out questionnaires to provide feedback on the dashboard's usability, functionality, and overall experience. They also offer suggestions for improvements, which are crucial for refining the dashboard based on practical user insights. This structured approach ensures a thorough evaluation and supports the continuous enhancement of the dashboard's performance and user experience.

1. **Read the Manual:** Practitioners will start by reading the user manual. This manual provides comprehensive instructions and information about the dashboard's features, functionalities, and navigation. Understanding the manual is crucial for participants to effectively use and evaluate the dashboard during the testing phase.
2. **Test the Dashboard Usage by Completing Assigned Tasks:** After reading the manual, practitioners will test the dashboard by completing a series of assigned tasks. These tasks are designed to evaluate different aspects of the dashboard's functionality:

   2.1 **View User Detail Section**: Practitioners will navigate to the user detail section of the dashboard. They will review the information presented to individual users, including personal details and exercise metrics. This task assesses how easily practitioners can access and interpret user-specific data.

   2.2 **View the Report of All Users**: Practitioners will access a comprehensive report section that summarizes data for all users, allowing them to analyze overall trends and patterns in exercise behavior. Additionally, they will examine detailed FITT (Frequency, Intensity, Time, and Type) reports for individual users. This evaluation assesses the dashboard's ability to aggregate and present collective data clearly while also providing in-depth, actionable insights into individual user performance

   2.3 **Record Information of Each User:** Practitioners will practice recording and updating information for individual users. This task tests the ease of entering and managing data within the dashboard, ensuring that user inputs are accurately captured and stored.
3. **Complete Questionnaires:** Participants will fill out questionnaires designed to gather their feedback on the dashboard's usability, functionality, and overall experience. The questionnaires will include questions on how intuitive the dashboard is, the clarity of the information presented, and any difficulties encountered during the tasks.
4. **Provide Feedback and Suggestions for Improvement:** After completing the tasks and questionnaires, participants will provide feedback on the dashboard. They will offer suggestions for improvements and adjustments to enhance the dashboard's performance

and user experience. This step is crucial for refining the dashboard based on practical user insights. The result of the feedback will be shown in Figure 32 and Table 8 below.

Table 8: Descriptive Score for Practitioners

User Group	Familiarity in Usage	Usability and Control	FITT Principle Integration	Usefulness
Physical Therapist	2.5	3.0	3.5	3.5
Physical Exercise Expert	4.0	4.0	4.5	4.5
Caregiver	1.5	3.5	3.0	3.0

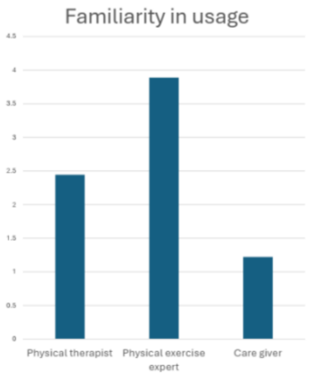
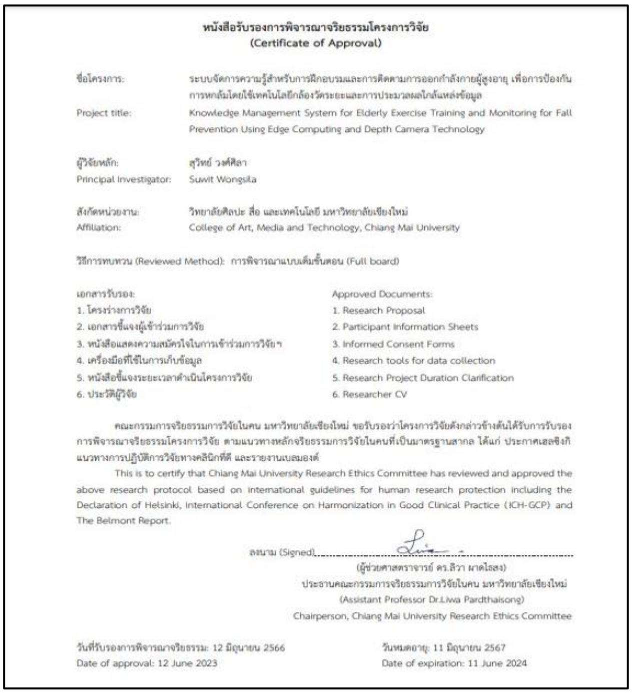


Figure 32: Feedback from the Practitioner

Ethics Approval

Before commencing our experiment, we took comprehensive steps to ensure that all ethical considerations were meticulously addressed. On June 12, 2023, we received full board ethics approval from the Chiang Mai University Research Ethics Committee in Figure 33. This rigorous approval process confirms that our research adheres to the highest ethical standards, ensuring the safety, privacy, and well-being of all participants involved. By securing this approval, we demonstrate our commitment to conducting research that is both ethically sound and respectful of the rights and dignity of those who contribute to our study.



หนังสือรับรองการพิจารณาจริยธรรมโครงการวิจัย
(Certificate of Approval)

ชื่อโครงการ: ระบบจัดการความรู้สำหรับการฝึกอบรมและการติดตามการออกกำลังกายผู้สูงอายุ เพื่อการป้องกันการหกล้มโดยใช้เทคโนโลยีกล้องวัดระยะและการประมวลผลใกล้แหล่งข้อมูล

Project title: Knowledge Management System for Elderly Exercise Training and Monitoring for Fall Prevention Using Edge Computing and Depth Camera Technology

ผู้วิจัยหลัก: สุวิทย์ วงศ์ศิลา

Principal Investigator: Suwit Wongsila

สังกัดหน่วยงาน: วิทยาลัยศิลปะ สื่อ และเทคโนโลยี มหาวิทยาลัยเชียงใหม่

Affiliation: College of Art, Media and Technology, Chiang Mai University

วิธีการทบทวน (Reviewed Method): การพิจารณาแบบเต็มขั้นตอน (Full board)

เอกสารรับรอง:	Approved Documents:
1. โครงร่างการวิจัย	1. Research Proposal
2. เอกสารชี้แจงผู้เข้าร่วมการวิจัย	2. Participant Information Sheets
3. หนังสือแสดงความสมัครใจในการเข้าร่วมการวิจัยฯ	3. Informed Consent Forms
4. เครื่องมือที่ใช้ในการเก็บข้อมูล	4. Research tools for data collection
5. หนังสือชี้แจงระยะเวลาดำเนินโครงการวิจัย	5. Research Project Duration Clarification
6. ประวัติผู้วิจัย	6. Researcher CV

คณะกรรมการจริยธรรมการวิจัยในคน มหาวิทยาลัยเชียงใหม่ ขอรับรองว่าโครงการวิจัยดังกล่าวข้างต้นได้รับการรับรองการพิจารณาจริยธรรมโครงการวิจัย ตามแนวทางหลักจริยธรรมการวิจัยในคนที่เป็นมาตรฐานสากล ได้แก่ ประกาศเฮลซิงกิ แนวทางการปฏิบัติการวิจัยทางคลินิกที่ดี และรายงานเบลมองต์

This is to certify that Chiang Mai University Research Ethics Committee has reviewed and approved the above research protocol based on international guidelines for human research protection including the Declaration of Helsinki, International Conference on Harmonization in Good Clinical Practice (ICH-GCP) and The Belmont Report.

ลงนาม (Signed)..
(ผู้ช่วยศาสตราจารย์ ดร.ลีวา ผาดไธสง)
ประธานคณะกรรมการจริยธรรมการวิจัยในคน มหาวิทยาลัยเชียงใหม่
(Assistant Professor Dr.Liwa Pardthaisong)
Chairperson, Chiang Mai University Research Ethics Committee

วันที่รับรองการพิจารณาจริยธรรม: 12 มิถุนายน 2566
Date of approval: 12 June 2023

วันหมดอายุ: 11 มิถุนายน 2567
Date of expiration: 11 June 2024

Figure 33: Certificate of Approval from CMU Ethics Committee

Screening for Test

Before participation, all candidates underwent the PAR-Q+ test to determine their eligibility. This test, administered by a physical therapist, assessed their readiness for physical activity, ensuring safety and appropriateness for the study. The Par-Q+ test included questions on heart conditions, chest pain, dizziness, bone/joint problems, and medication use, requiring a "no" answer to all questions to pass. Only those who scored 7 out of 7 on the test, indicating full readiness for physical activity, were included in the study.

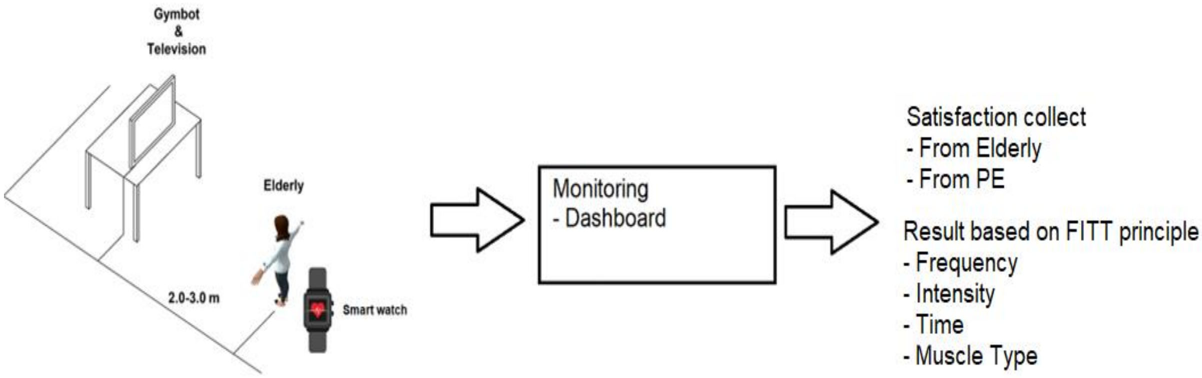


Figure 34: Experiment Set Up before Exercise

The TV will be positioned 2.0 to 3.0 meters away from the elderly participants to ensure comfortable viewing, and it will be connected to the GymBot system to display real-time exercise data. Each participant will be equipped with a GymBot, which features a 3D depth camera for motion analysis and fall detection, as well as a LilyGo smartwatch to monitor physical activity and heart rate in real time. This setup provides valuable physiological data during exercise sessions. The collected data will be integrated and visualized on a centralized monitoring dashboard, which is designed to track exercise performance according to the FITT principles (Frequency, Intensity, Time, and Type), enabling real-time adjustments and feedback.

Exercise Period

Participants were randomly divided into two cohorts, with 10 elderly individuals per cohort, through a computer-generated random number table to ensure unbiased distribution. Each group engaged in a three-week exercise regimen designed to improve balance, flexibility, and strength, based on the FITT principles (Frequency, Intensity, Time, and Type). The regimen included stretching, 21 selected postures, and cooldown exercises, developed collaboratively by experts and elderly participants. The exercises targeted both upper and lower body activities, with each session lasting approximately 60 minutes. In Cohort 1, Group 1 exercised on Monday, Wednesday, and Friday, while Group 2 exercised on Tuesday, Thursday, and Saturday, with all participants resting on Sundays. During these sessions, data were collected and transmitted to a centralized dashboard, providing real-time visualization of the participants' exercise performance and allowing for effective monitoring and adjustments by physical therapists and exercise professionals. Following the successful completion of Cohort 1, the study will proceed to Cohort 2, involving an additional 10 eligible elderly participants. The methodology for Cohort 2 will replicate the process used in Cohort 1, adhering to the same procedures outlined previously.

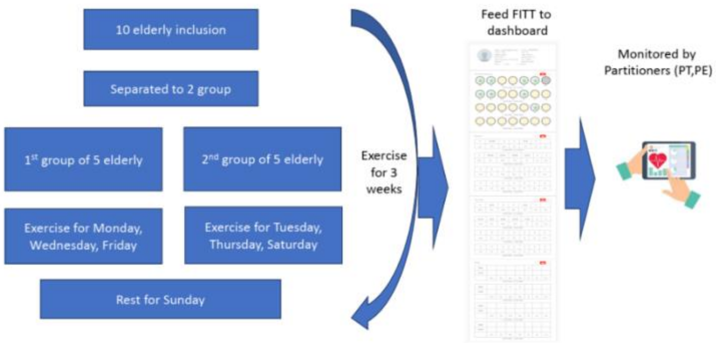


Figure 35: Schematic Overview of the Elderly Exercise Experiment

Data collection

The process of data collection in this study involved gathering and transmitting exercise data based on the FITT principles (Frequency, Intensity, Time, and Type) to a centralized dashboard. During each exercise session, detailed metrics were recorded, including the number of login times, the intensity and duration of the exercises, and the specific types of exercises performed by Sedaghati et al. (2022) [29]. This data was then fed into the dashboard, which served as a visual interface to display the information in a clear and organized manner. The dashboard enabled real-time monitoring and evaluation of the participants' performance, allowing for continuous tracking and adjustment of the exercise regimen to ensure its effectiveness and safety. The result of data collection is in Table 9 and Table 10 below.

Table 9: The Data collection from Cohort 1

User	Week	Frequency	Intensity	Time	Type of Muscle
User 1	Week 1	3	23.81	59.93	L
	Week 2	3	38.89	155.57	U
	Week 3	3	48.68	136.28	L
User 2	Week 1	3	57.81	59.28	U
	Week 2	3	70.83	78.12	U
	Week 3	3	60.76	80.48	U
User 3	Week 1	3	52.08	69.77	U
	Week 2	3	76.69	73.78	U
	Week 3	3	79.86	53.98	U
User 4	Week 1	3	53.37	80.71	U
	Week 2	3	47.51	76.40	U
	Week 3	3	44.40	59.48	U
User 5	Week 1	3	55.48	82.97	U
	Week 2	3	34.70	100.32	U
	Week 3	3	36.53	135.28	L
User 6	Week 1	3	33.11	70.08	U
	Week 2	3	37.23	107.82	U
	Week 3	3	48.92	152.87	U
User 7	Week 1	3	19.57	127.05	U
	Week 2	3	49.76	107.75	U
	Week 3	3	54.59	97.62	U
User 8	Week 1	3	44.52	71.23	L
	Week 2	3	41.55	130.58	L
	Week 3	3	35.62	89.00	U
User 9	Week 1	3	41.25	72.45	U
	Week 2	3	37.50	132.37	L
	Week 3	3	40.42	76.77	U
User 10	Week 1	3	44.36	60.25	U
	Week 2	3	47.56	53.00	U

User	Week	Frequency	Intensity	Time	Type of Muscle
	Week 3	3	31.18	53.50	U

Table 10: The Data collection from Cohort 2

User	Week	Frequency	Intensity	Time	Type of Muscle
User 11	Week 1	3	33.33	58.65	L
	Week 2	3	39.92	97.47	L
	Week 3	3	46.90	148.03	L
User 12	Week 1	3	58.24	51.90	L
	Week 2	3	69.02	106.24	U
	Week 3	3	71.77	108.97	U
User 13	Week 1	3	40.34	75.90	U
	Week 2	3	53.41	101.26	U
	Week 3	3	59.09	121.29	U
User 14	Week 1	3	51.09	41.61	U
	Week 2	3	54.71	106.91	U
	Week 3	3	64.13	123.10	U
User 15	Week 1	3	34.68	34.93	U
	Week 2	3	36.02	106.03	U
	Week 3	3	53.23	139.42	U
User 16	Week 1	3	34.55	57.15	L
	Week 2	3	49.67	106.03	U
	Week 3	3	44.55	100.65	U
User 17	Week 1	3	46.88	33.92	L
	Week 2	3	56.25	75.92	L
	Week 3	3	60.94	73.92	L
User 18	Week 1	3	41.67	101.78	U
	Week 2	3	41.67	128.62	U
	Week 3	3	48.33	105.45	U
User 19	Week 1	3	49.23	83.35	U
	Week 2	3	45.13	180.02	U
	Week 3	3	48.46	125.17	U
User 20	Week 1	3	64.64	81.78	L
	Week 2	3	59.35	148.47	L
	Week 3	3	71.34	118.97	L

Monitoring

The monitoring process in this study was a critical component to ensure the safety and effectiveness of the exercise interventions. The exercise data collected and displayed on the centralized dashboard was continuously overseen by practitioners, specifically Physical Therapists (PT) and Physical Exercise (PE) professionals. These practitioners utilized the dashboard to track the progress of each participant, ensuring that the exercises were being performed correctly and safely. Through real-time monitoring, they were able to provide immediate feedback and make necessary adjustments to the exercise routines as required. This proactive approach allowed for timely interventions, ensuring that the exercise program remained both safe and beneficial for the elderly participants, thereby maximizing the overall efficacy of the intervention by Freiberger et al. (2007)[12].

2.2.11.3 Classification of Elderly Groups

Fried Frailty Criteria

The Fried Frailty Criteria is a widely used set of guidelines for assessing frailty in older adults. Developed by Dr. Linda Fried and colleagues in 2001, it helps identify individuals at high risk of health decline, including frequent falls, hospitalization, or death. The criteria consist of 5 key components:

1. **Unintentional Weight Loss**: Loss of more than **4.5 kg (10 pounds)** or more than **5%** of body weight over the past 6 months, without intentional effort.
2. **Exhaustion**: Frequent feelings of exhaustion that impact the ability to perform daily activities.
3. **Slowness**: Decreased walking speed, slower than standard, typically measured over **4 meters** or more.
4. **Weakness**: Reduced muscle strength, commonly measured by decreased grip strength.
5. **Low Physical Activity**: Engaging in lower-than-standard levels of physical activity, often quantified by the number of calories burned per week.

Diagnosis

- **Frail**: Meets **3 or more** criteria.
- **Pre-frail**: Meets **1-2** criteria.
- **Non-frail**: Meets **none** of the criteria.

The Fried Frailty Criteria is a vital tool for healthcare providers and caregivers to manage and mitigate frailty-related risks in older adults.

Thai Frailty Index

The Thai Frailty Index is an assessment tool specifically designed to evaluate frailty in older adults within the Thai cultural and social context. It focuses on identifying older adults at risk of health decline, with attention to physical, mental, and social factors relevant to the Thai population.

1. **Physical Health**: Assessment of aspects such as muscle strength, walking speed, balance, and unintentional weight loss.
2. **Mental Health**: Evaluation of conditions like depression, anxiety, cognitive decline, or memory issues.
3. **Activities of Daily Living (ADL)**: Ability to perform daily tasks, including dressing, eating, and mobility.
4. **Social and Environmental Factors**: Consideration of social support, family involvement, access to healthcare, and living conditions.

Scoring and Classification

- **Non-frail**: Low scores indicate good health and independent functioning in daily activities.
- **Pre-frail**: Some signs of frailty, requiring monitoring and possible intervention.
- **Frail**: High scores indicate significant frailty, requiring more intensive care and support.

The Thai Frailty Index provides a comprehensive and culturally tailored approach to assessing frailty in older adults in Thailand. By considering physical, mental, and social factors, this tool enables healthcare providers to create care plans that meet the specific needs of elderly individuals in Thailand.

2.3 Future Advancements of the Pilot Case

The current shortcoming of this project is the challenge of effectively classifying samples using more than two parameters. Initially, we did not attempt to use more than two parameters, but when we did, the results did not align with our expectations; the 2D graph produced was not clear or meaningful.

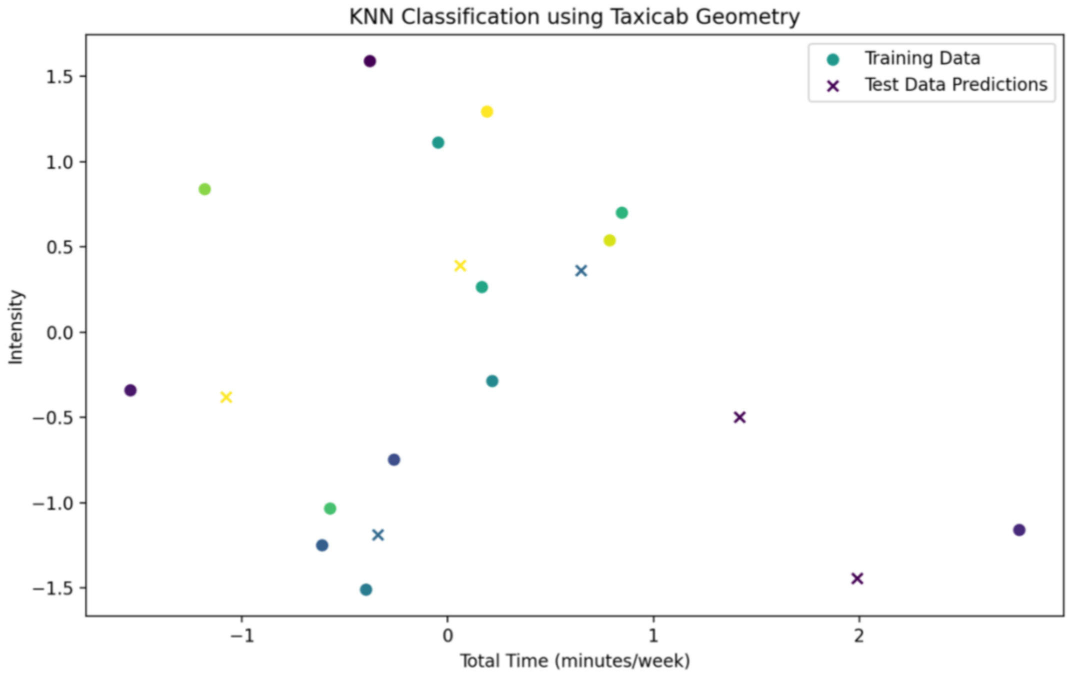


Figure 36: KNN Classification using Taxicab Geometry

This graph illustrates the result of our attempt to classify samples using more than two parameters in the K-Nearest Neighbors (KNN) model. The current shortcoming of this project is evident in the challenge of effectively classifying samples when adding additional parameters beyond two. Initially, we focused on using just two parameters but later decided to experiment with incorporating more. However, as shown in the graph, the results did not align with our expectations. The 2D graph, which now attempts to represent more complex data, appears unclear and lacks meaningful separation between the groups. This outcome highlights the difficulty of visualizing and interpreting the data when more than two parameters are used, leading us to conclude that sticking to two parameters for classification in a 2D space is more effective.

Color Definitions and Categories

1. **Dark Purple**

   Category: Low Intensity / Low Time Commitment

   Meaning: This category represents participants or data points with low exercise intensity and a minimal amount of time spent on physical activity. This group may include individuals who are just starting a fitness program or those who maintain a very light routine. Their activity level is generally lower compared to other groups.

2. **Yellow**

   Category: High Intensity / Low Time Commitment

Meaning: This category indicates participants who engage in high-intensity workouts but for a short duration. They may perform more intense exercises (e.g., high-intensity interval training - HIIT) but do not dedicate a large amount of time weekly to their routine. This group might be more focused on quick, effective workouts.

3. Green

Category: Moderate Intensity / Moderate Time Commitment

Meaning: This group reflects participants who balance their intensity and time. Their workout regimen is consistent and moderately demanding, involving a reasonable time commitment. These participants may aim for general fitness maintenance with steady progress in their endurance and strength.

4. Teal / Blue

Category: High Intensity / High Time Commitment

Meaning: This category represents individuals who invest both time and effort into their workouts. They engage in high-intensity exercises and dedicate a significant amount of time each week to their physical activity. This group may consist of advanced exercisers or athletes aiming for peak performance.

Consequently, we reverted to using just two parameters—frequency and time—for classification.

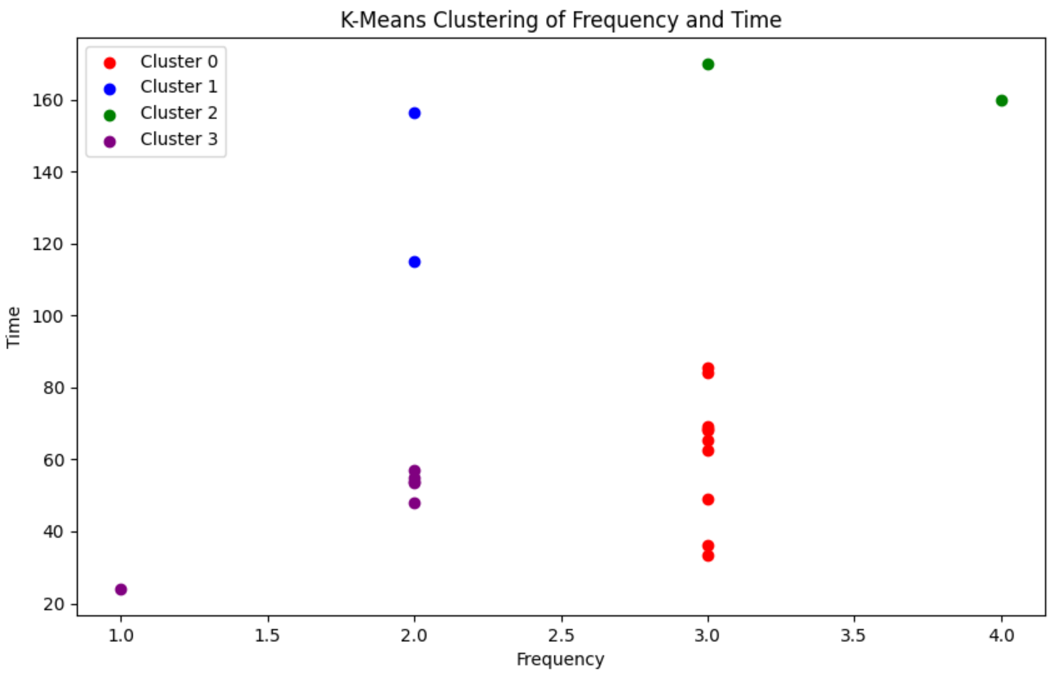


Figure 37: K-Means Clustering of Frequency and Time

The graph shown here represents the outcome after reverting to a simpler approach, using just two parameters—frequency and time—for classification. This graph utilizes K-Means clustering to categorize the data points based on these two parameters. As depicted, the data points are now clearly separated into four distinct clusters, each represented by a different color.

Moving forward, we aim to improve the model by consulting with physical therapists to understand their requirements. If they want the model to classify whether an individual is elderly, we can incorporate this criterion into the rule-based approach for more accurate and relevant classification.

Model Implementation

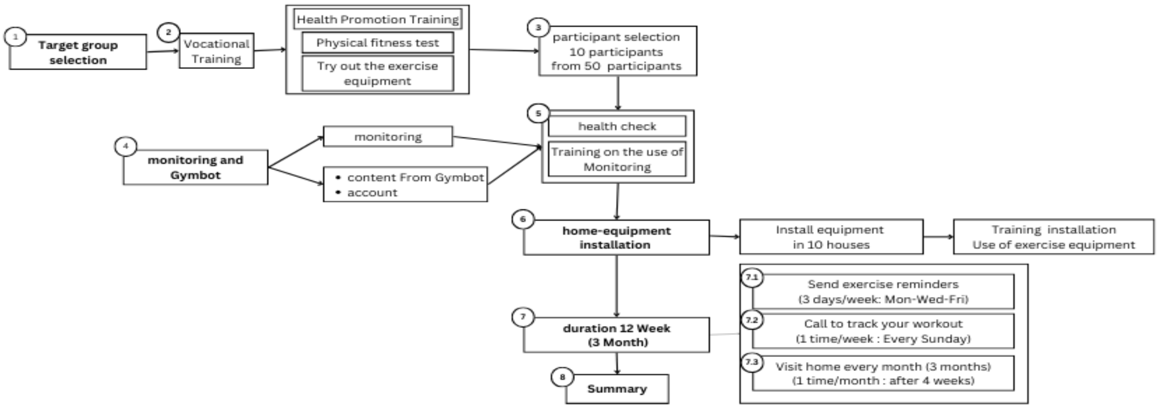


Figure 38: Model Implementation Plan

A flowchart outlining the steps of a project or program related to health promotion training and the installation of exercise equipment in homes. Here is an expanded explanation of each step based detailed description

While the simplification improved classification clarity, the project has future ambitions to evolve. By incorporating insights from physical therapists, we aim to refine the model further, potentially introducing rule-based approaches that accommodate the specific classification needs, such as determining whether an individual is elderly.

To enhance the model's capability and address the limitations of the pilot case, we propose using AI/ML algorithms to analyze and optimize the FITT (Frequency, Intensity, Time, Type) principle, a well-established framework in exercise science.

In this pilot case, the selection of the target group was highly specific, as participants needed to be ready and willing to have exercise equipment installed in their homes. This requirement stemmed from the need to assess the practicality of home-based fitness programs. In previous pilot cases, many participants were either reluctant or unable to integrate the exercise equipment into their daily routines, which revealed shortcomings in the initial recruitment process. To address these issues and ensure better results, the future project aimed to refine participant selection through a more structured and targeted approach.

The recruitment strategy will be improved by leveraging a vocational training program, which focused on individuals in health promotion-related fields. This program will provid an ideal platform for educating participants on maintaining physical health, particularly among elderly populations. As part of the program, participants undergo a physical fitness test, allowing the team to assess their baseline strength and overall physical condition. In addition to the fitness test, participants will be given the opportunity to try out the exercise equipment, familiarizing themselves with the tools they would later use at home by Sandvik et al. (1993) [27]. This approach will be implemented to avoid one of the major issues identified in previous pilots, where a lack of familiarity with the equipment often results in participants not fully utilizing it once it is installed.

To ensure that only the most suitable candidates are selected, participants complete a detailed readiness form, which assesses their willingness and ability to use home exercise equipment. Based on their responses, 10 participants will be chosen to take part in the program. These individuals demonstrate the commitment and readiness required to incorporate the equipment into their daily routines. This careful selection process marks a significant improvement over previous pilot cases, where less rigorous selection criteria lead to lower engagement and participation rates.

Once the participants are selected, the project team focuses on setting up a monitoring system to track progress. A dedicated platform will be created using Gymbot, a tool designed to log and analyze exercise routines. Each participant will have their own account, which allows both the participants and project administrators to monitor activity levels and provide real-time feedback. This system addresses previous issues of inconsistent reporting and lack of accountability, ensuring that all participants stay on track and are supported throughout the program.

In conjunction with the monitoring system, regular health checks will be conducted to assess participants' physical condition before and after they begin using the exercise equipment at home. These health checks are critical for evaluating the impact of the fitness regimen on participants' overall well-being. Moreover, participants will receive thorough training on how to use the monitoring tools, ensuring they can track their progress effectively and accurately report their workouts. This comprehensive approach addresses gaps identified in earlier pilot cases, where insufficient training often results in incorrect or incomplete data collection.

After the equipment is installed in participants' homes, the project will continue to provide support by dividing the 12-week exercise tracking period into a structured system of reminders and check-ins. Participants will be reminded to exercise three days a week, with additional weekly check-in calls to offer encouragement and track their progress. Furthermore, monthly home visits provide direct support and help resolve any issues with the equipment or the exercise routines. This multi-tiered approach ensures that participants remain engaged and motivated throughout the program, while also allowing the project team to monitor and adapt to any challenges.

At the conclusion of the 12-week period, a comprehensive summary of the exercise results will be compiled, including feedback on the use of the equipment, participants' health improvements, and overall project outcomes. This thorough evaluation process can provide valuable insights into the success of the program and allow for the identification of further areas for refinement. By integrating artificial intelligence and machine learning to analyze exercise patterns, the project is able to offer a detailed assessment of the effectiveness of the fitness regimen and suggest personalized recommendations for future participants.

In summary, using AI/ML to analyze FITT improvements from exercise can provide detailed, data-driven insights into how specific adjustments in exercise frequency, intensity, time, and type affect the fitness outcomes of a sample group. This allows for the optimization of exercise programs to achieve the best possible results.

This AI/ML-driven approach allows us to optimize exercise programs for participants, addressing the shortcomings highlighted in the pilot case. As we move forward, the aim is to offer more personalized, effective solutions for exercise classification and health monitoring. By reverting to a simpler approach of using just two parameters (frequency and time), the project has already demonstrated better clarity and classification accuracy. Moving forward, leveraging AI/ML to analyze the FITT principle will help to further improve the model's capability, enabling personalized and optimized exercise plans that address the initial shortcomings encountered with complex, multi-parameter classification.

2.4 Conclusion

The pilot case implementation of the elderly mobility monitoring and exercise system has demonstrated the significant potential of integrating digital health technologies in enhancing elderly care. By combining wearable devices, AI-driven analysis, and real-time monitoring tools, the system provides a robust platform for elderly individuals to engage in safe and effective exercise routines. The deployment of tools such as smartwatches and motion analysis dashboards has allowed for continuous tracking of key health metrics like heart rate, movement, and exercise intensity based on the FITT principles (Frequency, Intensity, Time, and Type).

Throughout the project, collaboration with healthcare practitioners has been essential in ensuring the system's usability and effectiveness. The real-time feedback mechanisms allow for immediate adjustments to exercise routines, ensuring that the elderly participants receive personalized recommendations tailored to their physical capabilities. This not only promotes physical health but also fosters greater independence among the elderly.

As we move forward, the insights gained from this pilot case will be critical in refining the system and expanding its application to other elderly care settings. Future work will focus on addressing current limitations, such as enhancing data analysis capabilities and ensuring broader accessibility to the technology. Ultimately, the project represents a significant step forward in the use of digital health tools to promote active aging and improve the quality of life for elderly individuals.

3 Pilot Case Implementation at MFU

3.1 Introduction

The MFU pilot case focuses on a fall-risk assessment which is an initial step for fall prevention. The original clinical assessment requires human interaction and records only time spent for each assessment which provides no insight to fall-risk level. This pilot case, therefore, developed a comprehensive fall-risk assessment system integrating IoT hardware and software to not only facilitate the assessment processes but also to collect the detailed testing data which subsequently will be processed by machine learning to infer the fall risk. This evaluation would assist the caretakers or healthcare practitioners to acknowledge the current mobility capacity of the elderly and the risk of falls. Then they could provide any intervention such as a proper treatment or exercise so that the elderly become healthier or stronger. Consequently, the treated elderly could repeat the fall-risk assessment for reevaluation and the caretaker could observe whether they have better mobility or not by Voukelatos et al. (2007)[33].

3.2 System Architecture

To evaluate the fall risk, MFU designed a complete system including both hardware and software integrated into a fall-risk assessment platform based on a clinical fall-risk measurement namely the Short Physical Performance Battery (SPPB) and the Timed Up and Go test (TUG). The overall system architecture is presented in Figure 39.

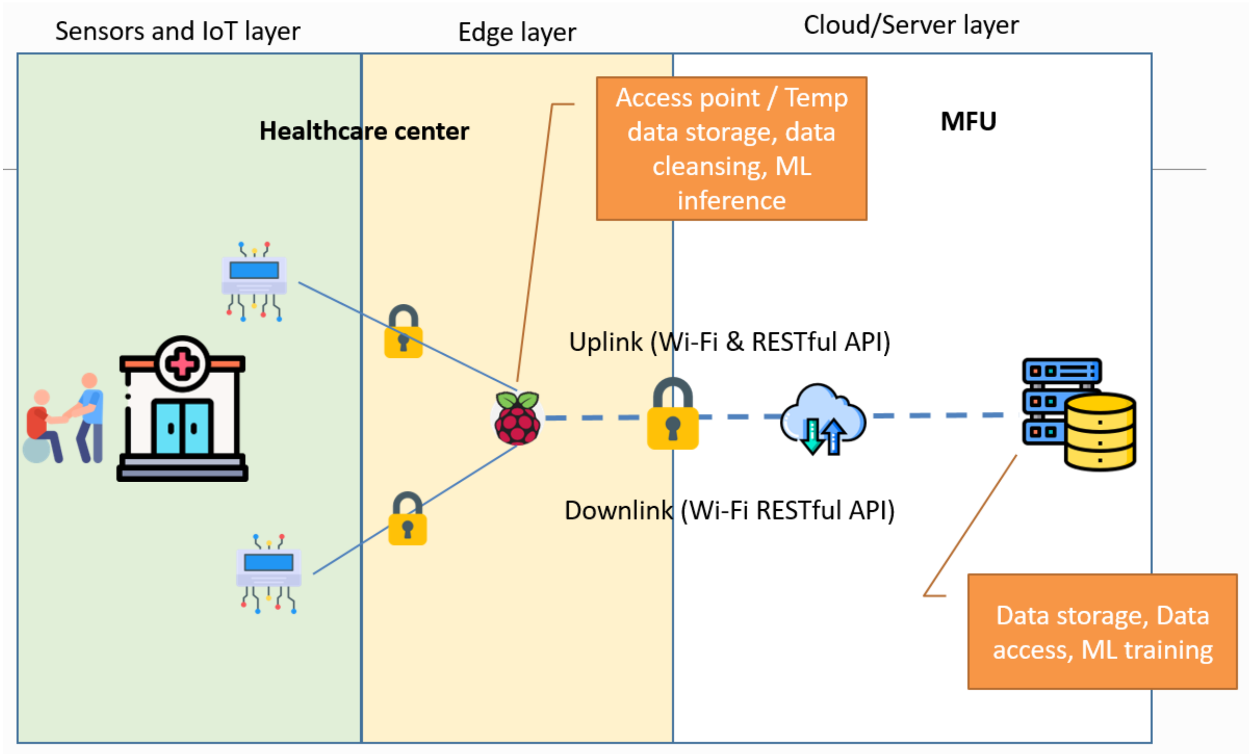


Figure 39: Overall System Architecture

The architecture was designed based on key principles i.e. data collection, data storage, data processing, data analysis, and data communication. It consists of three major layers which are the sensors and Internet of Things (IoT) layer, Edge layer, and Cloud/Server layer and all are connected through secured wireless communication. The details of each layer are as follows.

3.2.1 Sensors and IoT layer

This layer concentrates on developing hardware including embedded sensors and IoT devices to comply with the clinical measurement standard. Under the supervision and instructions of healthcare practitioners, three sets of devices were created as follows.

Sit Plate

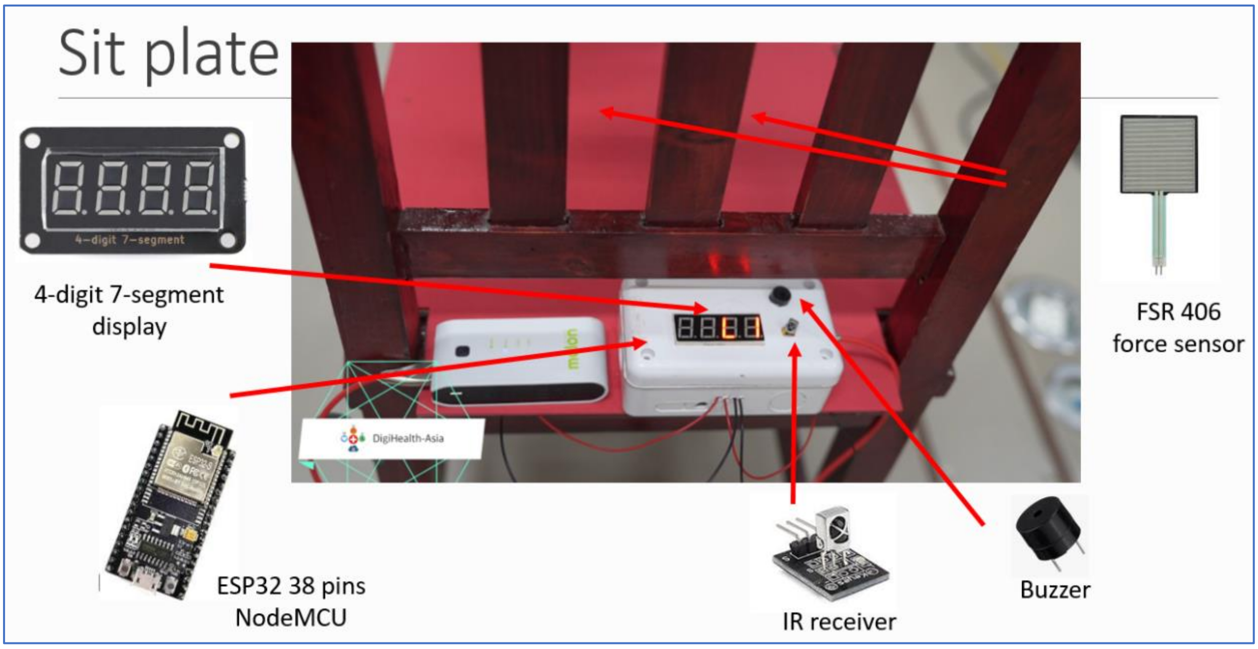


Figure 40: Sit plate

Figure 40 illustrates the sit plate device and its components. This device is built for two clinical tests: The chair stand test and the Time Up and Go (TUG) test. The device is in the shape of a flat plate consisting of two layers. The top layer is a soft material for comfortable sitting and the bottom layer is a strong acrylic plate for keeping pressure while a person is sitting on it. Between these layers, two force sensors FSR406 are inserted to monitor the pressure variation, and they are wired to the ESP32 microcontroller and other electronic components including the IR receiver, buzzer, and a 4-digit LED display. The sit plate was designed to be portable and could be fitted to a wooden chair that is normally used for the classical clinical test.

Gait Detection Device

For the standard gait test, the test person must walk for 4 meters whilst the time taken is being recorded. The gait detection device was designed to perform this measurement automatically as illustrated in Figure 41. In general, this device is attached to a tripod for height adjustability and portability. Internally, its key component is a LiDAR module which emits a laser that reflects on an object, the module then receives the reflected light and computes the estimated distance to the object. This sensor is controlled by an ESP32 microcontroller which connects to other electronic devices including an IR receiver, LED, and 4-digit display for input and output.

Figure 41: Gait detection device

Insole Device

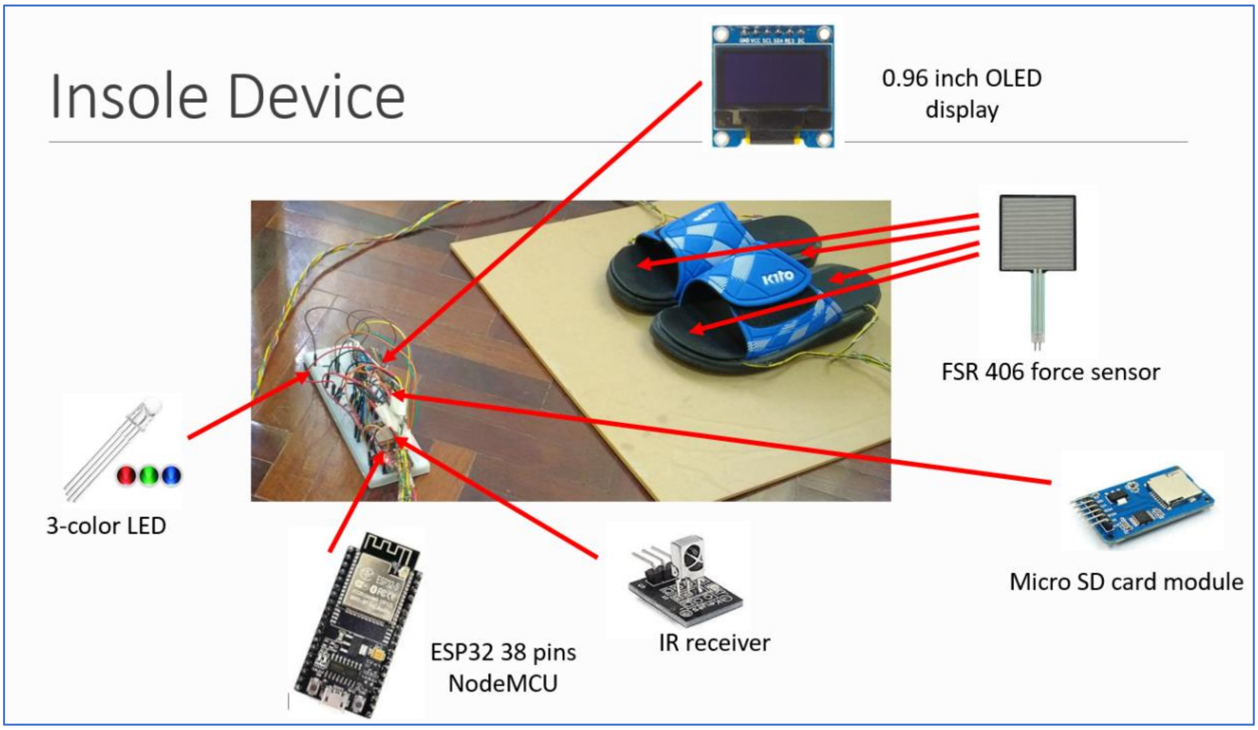


Figure 42: Insole device

The insole device is presented in Figure 42. Its main purpose is to measure the balance of a person standing in three postures being a side-by-side stand, semi-tandem stand, and full-tandem stand. Two insoles were used, one for the left shoe and one for the right shoe. Each insole is attached with two FRS406 force sensors to estimate the foot pressure which then is transferred to an ESP32 microcontroller's analog channel through physical wires. The data is then stored on a micro-SD card. Also, the microcontroller links to other electronic devices for input and output including an LED, IR receiver, and OLED display.

3.2.2 Edge Layer

The edge layer is an intermediate layer between the device and the server. It performs two-way communication i.e. forward and backward between those two layers. The main tasks of the edge layer are:

- Acting as a communication gateway for IoT devices
- Getting raw data from the IoT devices
- Preprocessing the data
- Storing the data temporarily for processing
- Sending the processed data to the server
- Getting/Updating the machine learning model from the server
- Performing machine learning inference
- Publishing the inference result to the IoT device

To support all the above tasks, a Raspberry PI 4 model B depicted in Figure 43 was chosen. It has sufficient capabilities for networking, data storage, data processing, and machine learning inference for this pilot case its requirements. In addition, it is compact, affordable, and robust for real onsite implementation. The edge layer communicates with the IoT layer via a secured HTTPS based RESTful API over Wi-Fi.

Figure 43: Raspberry Pi 4 Model B for the edge layer

3.2.3 Cloud/Server layer

On this layer, an MFU dedicated server was implemented to ensure data privacy according to the Thailand Personal Data Protection Act (PDPA). To be compatible with the communication between the IoT layer and the edge layer, the data of the elderly is transferred securely through the HTTPS based RESTful API from the edge layer to the server. The main tasks of the server layer are:

- To receive and store the processed data from the edge layer.
- To serve the collected data to the elderly's caretakers and MFU researchers as a website
- To train the machine learning models
- To transfer the trained machine learning model back to the edge layer for further inference

Communication among the three layers: the IoT layer, the edge layer, and the server layer will happen automatically in case of either a new test at the IoT layer occurs or a newly trained machine learning model is pushed to the server layer.

3.2.4 Dataset Collection and Analysis

Through a collaboration with a local municipality, Nanglae, the researchers partnered with the Nanglae Elderly center. Under the partner's agreement and the research ethics' approval, the researchers were allowed to perform the fall-risk assessment on the elderly in the Nanglae district, zone 16 located around 16 km from MFU as shown in Figures Figure 44 and Figure 45.

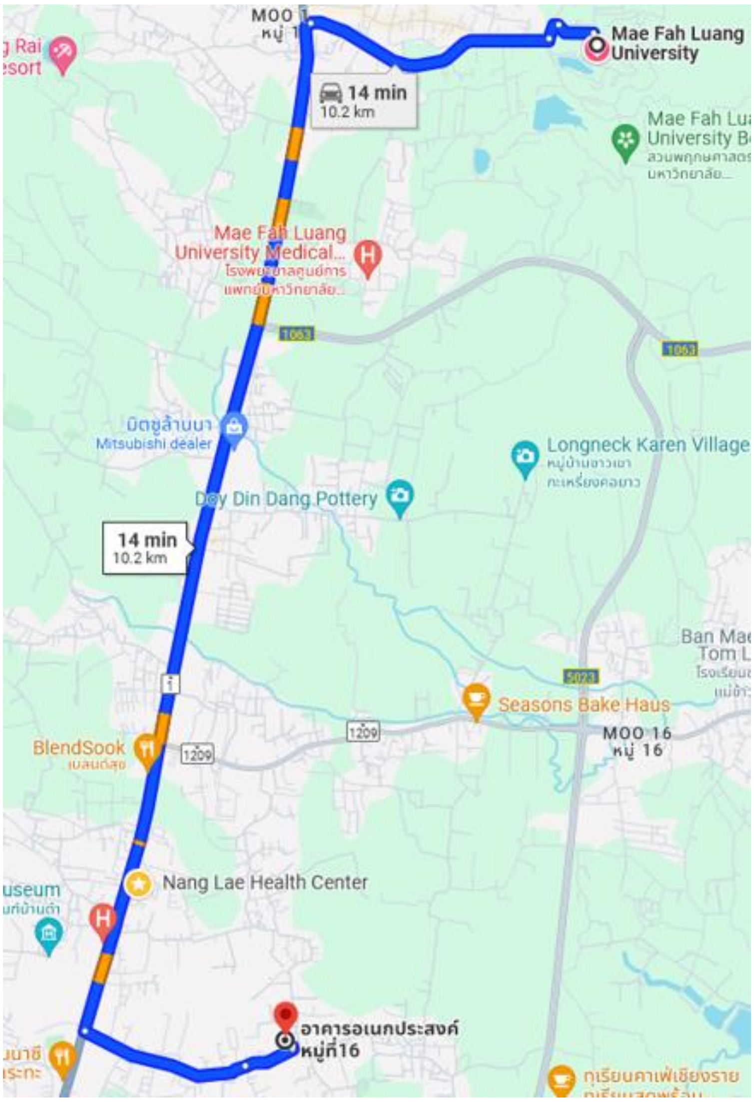


Figure 44: Location for Data Collection at Nanglae District, Zone 16

Figure 45: Overview of Data Collection Site

The data collection was set for 7 times as follows:

- 1st time on December 16, 2023 (student volunteers)
- 2nd time on December 23, 2023 (student volunteers)
- 3rd time on December 28, 2023 (elderly volunteers)
- 4th time on January 4, 2024 (elderly volunteers)
- 5th time on June 18, 2024 (elderly volunteers)
- 6th time on July 8, 2024 (elderly volunteers)
- 7th time on July 30, 2024 (elderly volunteers)

The first two data collections were for testing the IoT devices and the system. Therefore, the testers were planned to be student volunteers who could provide feedback to the researchers. Later the system was improved and implemented for the real data collection on the 3rd to 7th time under the instruction and supervision of the healthcare expert.

The details and the results of the data collection could be summarized as follows.

- The participants were 33 seniors aged between 60-75 years old.
- There were four main tests: chair stand test, time up and go test, gait speed test, and balanced test. For the first three tests, only times spent to complete the missions were recorded.

For a balanced evaluation, there were 3 subtests, and each subtest was repeated twice.

- Each record contains time-series data for 10 seconds at 5 Hz or around 50 data points
- In total, there were 308 records after data cleaning. All were labeled into three classes by the expert which are 1) Balanced (BL) 2) Imbalanced without sway (IWS) and 3) Imbalanced with sway (IS).
- The class distribution was 142, 116, and 50 records, or 46%, 38%, and 16% respectively.
- No missing data, data are cleansed for failed tests

The data collection environment is illustrated in Figure 46.

Figure 46: Data Collection Environment

The principal data for machine learning are from the balance test using the insole IoT device. The collected data was composed of the four pressure values bottom left (BL), top left (TL), top right (TR), and bottom right (BR) as shown in Figure 47. Each test was also recorded as a successful test, or a failed test based on the fact that the tester could keep the balance for the whole test or not.

After collecting data, the raw data needs preprocessing steps to remove the failed cases and then they were transformed into a format suitable for machine learning. An example of the transformed data is presented in Figure 48. Observe that for the records or rows, the odd rows represent the left foot's data while the even rows refer to the right foot's data. Each data point is an average of the two sensors embedded in either the left or the right insole. Additionally, the column represents the sampled data recorded from the sensors at an interval of 5 Hz. Therefore, there are a total of 50 columns (features) for each record.

To prepare the data for application in the machine learning algorithms, the data requires labels. The researchers visualized the data and asked healthcare experts to label each data record into three classes: 1) Balanced (BL) 2) Imbalanced without sway (IWS) and 3) Imbalanced with sway (IS) as illustrated in Figure 49 and Figure 50.

```
BL,TL,TR,BR
2756,1482,816,2411
2767,1409,735,2403
2768,1453,720,2415
2783,1451,699,2404
2779,1480,636,2416
2781,1520,656,2411
2782,1535,682,2406
2784,1587,701,2426
2783,1533,656,2418
2771,1680,720,2361
2768,1684,742,2363
2768,1699,838,2378
```

```
2777,1750,735,2384
2773,1650,810,2415
2773,1600,720,2402
2789,1655,741,2385
2785,1673,773,2398
2769,1747,852,2345
2782,1719,806,2358
2786,1708,770,2367
2800,1696,751,2415
2791,1790,731,2347
score = 1
----- success mode 1 -----
2474,1669,1206,1278
2448,1726,1271,1230
2444,1761,1375,1165
2454,1769,1422,1143
```

Successful test!

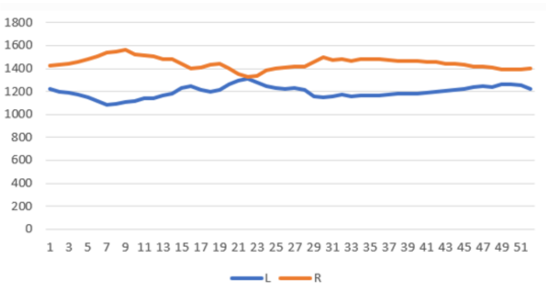
```
----- success mode 1 -----
524,2045,542,820
541,2070,544,803
620,2129,640,656
354,2149,507,485
time = 0.82
score = 0
----- fail mode 2 -----
```

Failed test!

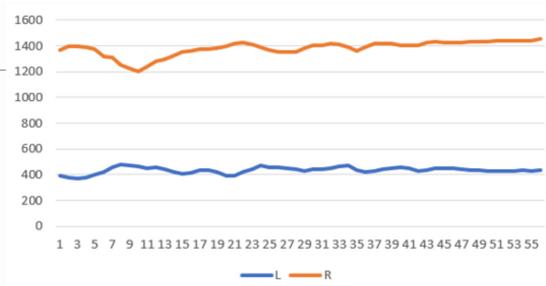
Figure 47: Example of Raw Data

		Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Feature 7
	1	0.0	1.0	2.0	3.0	4.0	5.0	
Left →	2	2119.0	2088.0	2110.5	2117.0	2129.5	2150.5	2[illegible]
Right →	3	1613.5	1569.0	1567.5	1551.5	1526.0	1533.5	1[illegible]
	4	2071.5	2087.0	2102.5	2111.5	2113.0	2129.5	2[illegible]
	5	1242.0	1250.5	1270.0	1282.5	1275.0	1250.5	1[illegible]
	6	1866.0	1844.5	1853.0	1852.0	1880.0	1808.0	1[illegible]
	7	1638.0	1622.5	1632.0	1648.0	1647.5	1634.5	1[illegible]
	8	1506.5	1481.0	1495.0	1500.5	1505.5	1533.5	1[illegible]

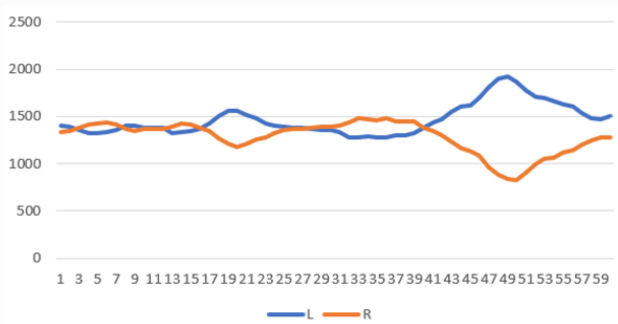
Figure 48: Example of Transformed Data



Class 1: Balance



Class 2: Imbalance, no sway



Class 3: Imbalance, sway

Figure 49: Three Classes (labels) of Data

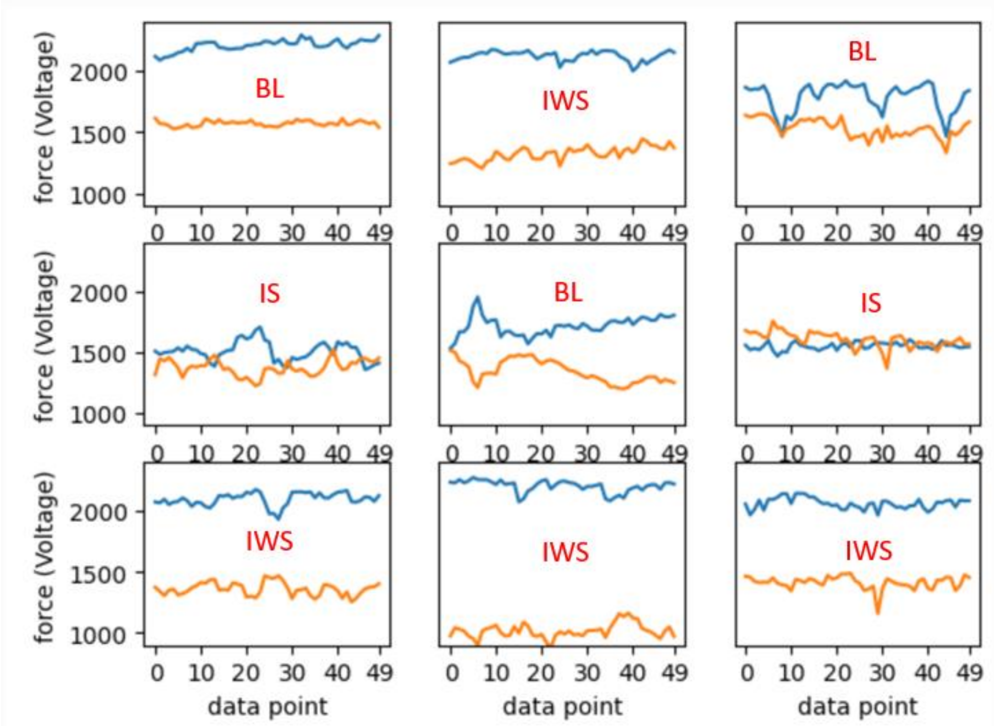


Figure 50: Data Visualization and Labelling of 9 Samples

3.2.5 ML Training

It is evident that the objective of using machine learning (ML) for the collected data in the MFU pilot case is to classify the balance of the elderly, therefore, the machine learning task is a classification task. The input is left and right foot time series data with the label from the healthcare expert as one of three possible classes. To proceed, it is mandatory to split the data into training data and testing data. Nevertheless, due to a rather limited amount of data which is a total of 308 records, instead of splitting the data to a ratio such as 70:30 or 80:20 for training and testing, it is more reasonable to adopt a cross-validation strategy. Here, 5-fold cross-validation was chosen and it split the data into 5 parts: 4 parts for training and 1 part for testing and then rotated the training and testing to each part of the data 5 times.

For the ML model, in classification, there are several possible ML approaches. Due to the limited data size, only 308 samples were available in total, using a deep learning model was not feasible. Hence, in this research, four well-known classical ML models were used which are 1) k-nearest neighbor (kNN), 2) Support Vector Machine (SVM), 3) Random Forest, and 4) Naïve Bayes.

Regarding feature engineering, all these ML models require scalar features to be extracted from the raw time-series data. Seeing from the raw 50 features as indicated in Figure 48, it is better to either compute new features from them or reduce the number of dimensions. Here the researchers opted for the latter to transform the number of dimensions using Principal Component Analysis (PCA) so that it could be visualized in a 2D plot, and it could assist us to see the class distribution. Firstly each feature was normalized and then PCA was applied for two distinct experiments. The first experiments transformed the left-foot data to one component and the right-foot data to another component. Then these two components were used as features for classification. Another experiment started with computing the difference between the raw left-foot and right-foot time-series data. Next PCA was implemented to reduce the number of dimensions to two for the classification by Cerri et al. (2003) [7].

3.2.6 Analysis of the Results

The data analysis was done in two phases according to the data collection period. For the second phase, the collected data are not yet fully labelled. The first batch of data was from the 3rd and the 4th data collection in December 2023 and January 2024 respectively. There are a total of 208 records, labeling in 3 classes of 112, 86, and 18 records or 52%, 40%, and 8% respectively. After the feature's dimension reduction, the data of the left foot and right foot were scatter-plotted and colored by classes as shown in Figure 51.

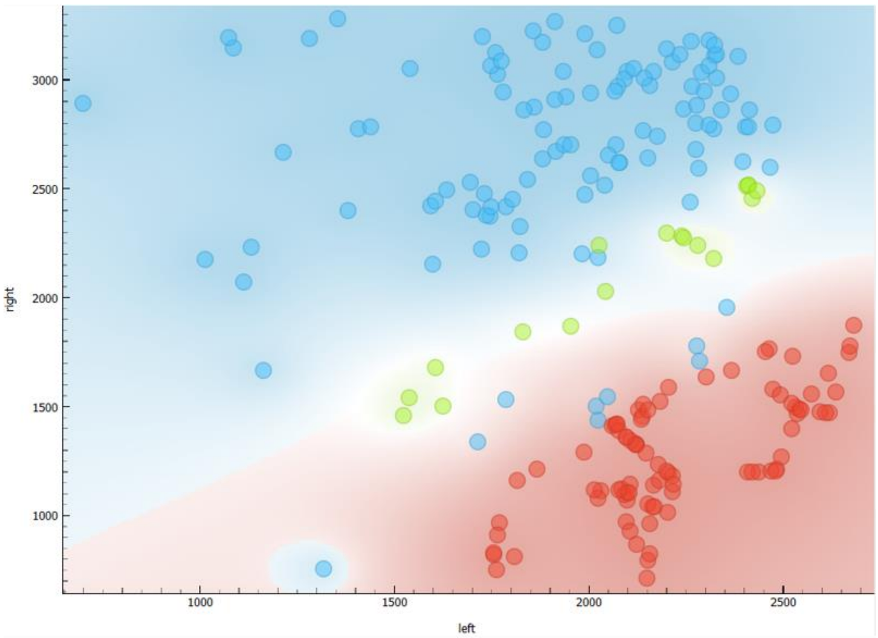


Figure 51: Data Visualization by Classes

It can be seen from Figure 51 that the three classes i.e. 1) balanced (BL), 2) imbalanced without sway (IWS) and 3) imbalanced with sway (IS) labelled by blue, red and green respectively are rather clear. The boundaries are noticeable though there were some overlaps. The green class (IS) has only few samples and is not easily clusterable. A major cause of this result could be due to the imbalanced dataset whose class IS percentage is merely 8%. Nevertheless, the data was classified and then evaluated as presented in Figure 52.

5-fold cross validation, 2 features (left, right)

Model	AUC	CA	F1	Prec	Recall
kNN (2)	0.990	0.907	0.908	0.913	0.907
SVM (2)	0.983	0.889	0.851	0.815	0.889
Random Forest (2)	0.981	0.907	0.902	0.904	0.907
Naive Bayes (2)	0.943	0.875	0.837	0.802	0.875

Predicted

Actual	1	2	3	Σ
1	97	7	8	112
2	0	86	0	86
3	5	0	13	18
Σ	102	93	21	216

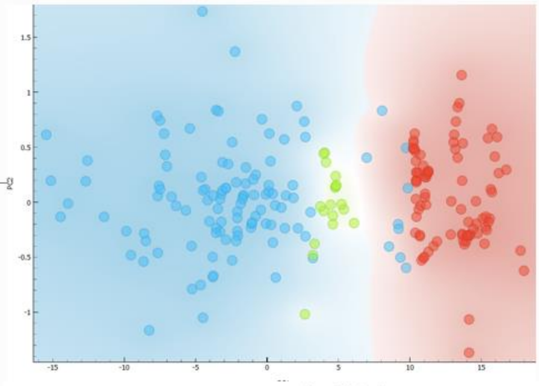
Predicted

Actual	1	2	3	Σ
1	102	8	2	112
2	1	85	0	86
3	9	0	9	18
Σ	112	93	11	216

Figure 52: Performance Matrix and Confusion Matrix

From Figure 52, kNN and random forest are likely to be the most accurate models since the Class Accuracy (CA) of both models is the highest at 90.7%. Nonetheless, kNN wins against random forest for overall performance because of its better F1 score. From the confusion matrix, kNN is superior to random forest for the classification of class INS and class IWS.

To improve the classification performance, new features were created based on the knowledge that balance is defined by the difference between left and right pressures. Thus, we subtracted the data of the left pressure from the ones of the right pressure and then reduced the result to two points using Principal Component Analysis (PCA) for the classification. The new data visualization and classification are shown in Figure 53.



5-fold cross validation, 2 features (Differences of left and right and reduced dimension to 2)

Model	AUC	CA	F1	Prec	Recall
Random Forest (8)	0.993	0.972	0.972	0.972	0.972
kNN (6)	0.999	0.954	0.954	0.955	0.954
SVM (6)	0.985	0.884	0.859	0.869	0.884
Naive Bayes (6)	0.946	0.870	0.851	0.846	0.870

Predicted

Actual	1	2	3	Σ
1	109	2	1	112
2	0	86	0	86
3	3	0	15	18
Σ	112	88	16	216

Figure 53: Classification Performance using Difference Feature

Figure 53 exhibits the scatter plot where the class boundary seems to be clearer than the one in Figure 51. Moreover, the classification accuracy now climbs to 97.2% for random forests. Misclassifications observed from the confusion matrix become fewer than before.

The researchers continued to adjust the number of reduced features based on PCA to observe if adding more features could improve the performance. It revealed that increasing the number of components did not affect the performance significantly.

A potential way to enhance classification performance is to expand the dataset, focusing on collecting more examples from the less frequent category, especially on the minority class or class IS (imbalanced with sway). According to the plan, the second batch of data was collected on July 8 and July 30, 2024, and parts of the data were labeled by the experts. Currently, the dataset has grown to 308 records and is composed of 142, 116, and 50 records, or 46%, 38%, and 16% from classes BL, IWS, and IS respectively. Still, the class distribution remained imbalanced, but its class ratios were better than the original data.

Figure 54 visualizes the 2D scatter plot of the original batch and the current batch. With more data in every class especially class 3, the class boundaries seem to show clear-cut patterns.

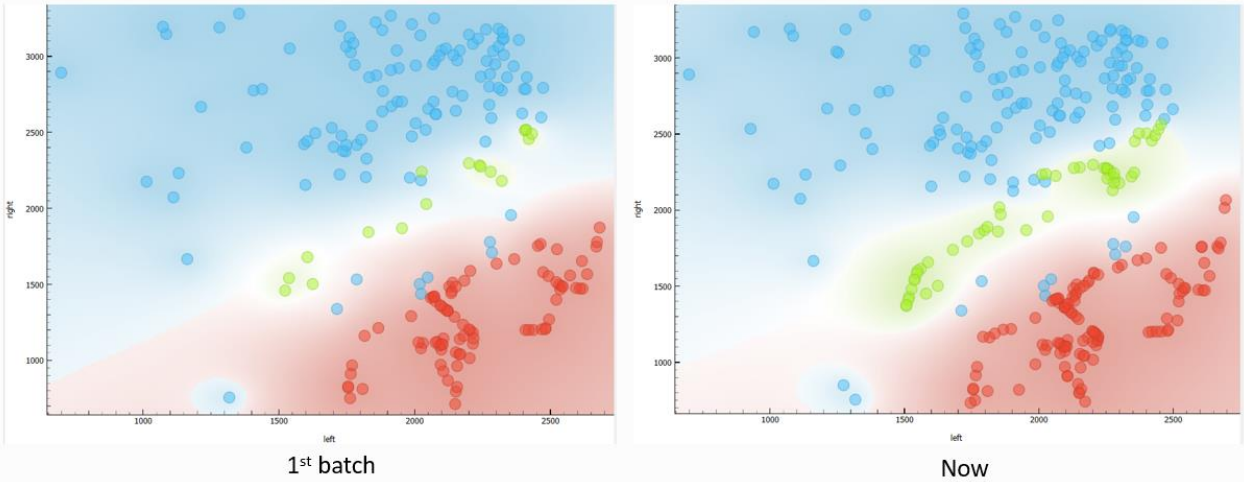


Figure 54: Visualization of 1st Batch and Current Data

From this insight, we repeated the classification using two different kinds of features. One is features from left and right foot pressures and the other is features extracted from the difference of two feet. The results are demonstrated in Figure 55 and Figure 56.

5-fold cross validation, 2 features (left, right)

Model	AUC	CA	F1	Prec	Recall
kNN (3)	0.996	0.955	0.954	0.957	0.955
SVM (3)	0.991	0.942	0.942	0.946	0.942
Random Forest (3)	0.995	0.951	0.951	0.951	0.951
Naive Bayes (3)	0.939	0.834	0.814	0.824	0.834

Predicted

Actual	1	2	3	Σ
1	129	8	5	142
2	0	116	0	116
3	1	0	49	50
Σ	130	124	54	308

Figure 55: Classification Performance of Current Data based on Left and Right Pressures

5-fold cross validation, 2 features (Differences of left and right and reduced dimension to 2)

Model	AUC	CA	F1	Prec	Recall
Random Forest (9)	0.996	0.987	0.987	0.988	0.987
kNN (7)	0.997	0.968	0.968	0.970	0.968
SVM (7)	0.987	0.925	0.925	0.927	0.925
Naive Bayes (7)	0.936	0.828	0.812	0.810	0.828

Predicted

Actual	1	2	3	Σ
1	138	0	4	142
2	0	116	0	116
3	0	0	50	50
Σ	138	116	54	308

Figure 56: Classification Performance of Current Data based on Difference of Pressures

It is seen that getting more balanced data helps improve classification performance. As shown in Figure 56, the classification accuracy and F1 score now reach 98.7% and increase by 1.5% from the original data. Only a few misclassifications were observed in class 1 (BL) and no misclassifications were found in classes 2 (IWS) and 3 (IS).

3.3 Future Advancements of the Pilot Case

At present, the collected data are not yet fully labeled. The researchers expect to get more labeled data from the healthcare experts and repeat the classification to observe the new performance. It is estimated that if the data size augments and the classes are more balanced, the classification performance could become better.

For future research, there is room for exploration. For example, the imbalanced dataset could be treated and upscaled using balancing strategies such as SMOTE to improve the classification performance. In addition, feature engineering should be investigated further to extract more relevant features. Also, the classification models must be optimized by fine-tuning the models' parameters. Lastly, with more data becoming available, it is worth exploring some deep learning strategies such as few-shot learning and long short-term memory (LSTM) learning.

3.4 Conclusion

The pilot case implementation at MFU is an integrated system for fall risk assessment. It comprises both hardware and software integrated into three connected layers: IoT layer, edge layer, and server layer. Each layer passes the data forward to and backward from the connected layer through a Wi-Fi network relying on a secured https protocol.

The system for the pilot case was implemented on a real-world site in a local area namely Nanglae. 33 seniors volunteered and participated in five experiments. A total of 308 data records were collected and labeled by the healthcare experts. The data were processed and then classified with different ML models. The final classification shows a promising performance of 98.7% classification accuracy.

Though some limitations remain, it is expected that with the promising outcomes of the pilot case and the support of related partners, soon the researchers would gain more data and more insights into research in this domain which would significantly enhance the fall risk assessment.

4 Conclusion and Future Work

The pilot cases at Chiang Mai University (CMU) and Mae Fah Luang University (MFU) have made substantial contributions to advancing fall prevention and elderly care through digital health technologies. Each pilot has demonstrated the effective integration of technology to address critical aspects of elderly health management by Ministry of Public Health (2019) [25].

Pilot Case 1: CMU The pilot case at CMU introduced a mobility monitoring and exercise system that combines wearable devices, AI-driven analysis, and real-time feedback. This system enabled continuous tracking of essential health metrics—such as heart rate, movement, and exercise intensity—based on the FITT principles (Frequency, Intensity, Time, and Type). The collaboration with healthcare practitioners ensured the system's practical effectiveness and usability, allowing for real-time adjustments and personalized recommendations. This approach has significantly contributed to improving physical health and promoting independence among elderly participants. Despite challenges in classifying data with multiple parameters, the project has paved the way for further refinement and broader application. The insights gained from this pilot will be critical for enhancing data analysis capabilities and addressing classification issues to optimize system performance.

Pilot Case 2: MFU At MFU, the implementation of an integrated fall-risk assessment system demonstrated exceptional performance, with a classification accuracy of 98.7%. The system's architecture, comprising IoT, edge, and server layers, effectively managed data collection and analysis. The pilot, conducted in Nanglae with 33 senior participants, provided valuable data that highlighted the system's potential for improving fall risk assessments. While there are limitations related to data labelling and dataset imbalance, the promising outcomes underscore the system's effectiveness and potential for further development. Continued support and research are expected to enhance the system's capabilities and expand its application.

Future Work

For Pilot Case 1 (CMU) Future work will address the current challenge of classifying samples with multiple parameters. Collaborating with physical therapists will help refine the classification model, potentially incorporating additional criteria for more accurate results. The project will also focus on enhancing data analysis capabilities, optimizing classification approaches, and exploring the integration of more complex parameters. Expanding the system's application to a broader range of elderly care settings will be essential for maximizing its impact on active aging and quality of life.

For Pilot Case 2 (MFU) Future research at MFU will prioritize obtaining more labelled data and addressing dataset imbalance through strategies like SMOTE. Enhancing feature engineering to identify effective features and optimizing classification models through fine-tuning will be crucial. The exploration of advanced deep learning techniques, including few-shot learning and Long Short-Term Memory (LSTM) networks, will be considered to improve classification performance and overcome current dataset limitations. These efforts aim to refine the fall-risk assessment system and increase its effectiveness in predicting and preventing falls among the elderly.

References

[1] A Prasert, "Elderly People Health problem and protection" Bangkok: union creation, 1979.
[2] Allaire, J.C.; McLaughlin, A.C.; Trujillo, A.; Whitlock, L.A.; LaPorte, L.; Gandy, M. Successful aging through digital games: Socioemotional differences between older adult gamers and non-gamers. Comput. Hum. Behav. 2013, 29, 1302–1306.
[3] Barnett A, Smith B, Lord S et al. Community-based group exercise improves balance and reduces falls in at-risk older people: A randomized controlled trial. Age Ageing 2003; 32:407–414
[4] Baldissera F, Cavallari P, Civaschi P. Preferential coupling between voluntary movements of ipsilateral limbs. Neurosci Lett 1982;34(1):95–100. [PubMed: 7162702]
[5] Ballesteros ML, Buchthal F, Rosenfalck P. The Pattern of Muscular Activity during the Arm Swing of Natural Walking. Acta Physiol Scand 1965; 63:296–310. [PubMed: 14329151]
[6] Balter JE, Zehr EP. Neural coupling between the arms and legs during rhythmic locomotor-like cycling movement. J Neurophysiol 2007;97(2):1809–18. [PubMed: 17065245]
[7] Cerri G, Borroni P, Baldissera F. Cyclic h-reflex modulation in resting forearm related to contractions of foot movers, not to foot movement. J Neurophysiol 2003;90(1):81–8. [PubMed: 12634273]
[8] Choi, Jihea, et al. "Posture management program based on theory of planned behavior for adolescents with mild idiopathic scoliosis." Asian Nursing Research 7.3 (2013): 120-127.
[9] Chusak Wechaphaet. (1995). *Exercise science principles.* Bangkok: Chulalongkorn University Press.
[10] Dietz V. Do human bipeds use quadrupedal coordination? Trends Neurosci 2002;25(9):462–7.
[11] Dietz V, Fouad K, Bastiaanse CM. Neuronal coordination of arm and leg movements during human locomotion. Eur J Neurosci 2001;14(11):1906–14. [PubMed: 11860485]
[12] Freiberger E, Menz HB, Abu-Omar K et al. Preventing falls in physically active community-dwelling older people: A comparison of two intervention techniques. Gerontology 2007;53:298–305.
[13] Fried, L.P.; Kronmal, R.A.; Newman, A.B.; Bild, D.E.; Mittelmark, M.B.; Polak, J.F.; Robbins, J.A.; [14] Gardin, J.M. Risk factors for 5-year mortality in older adults. JAMA 1998, 279, 585–592.

[15] Giam, C.K. and Teh, K.C. 1988. Sports Medicine, Exercise and Fitness : A Guide for Everyone. Springer: P.G.Publishing.

[16] Huang HJ, Ferris DP. Neural coupling between upper and lower limbs during recumbent stepping. J Appl Physiol 2004;97(4):1299–308.

[17] Johnson, J. 1985. Exercise, Aging and Health. Occupational Health Nursing. 3(11): 137-139.

[18] Jung, Daekyo, et al. "Conceptual framework of an intelligent decision support system for smart city disaster management." Applied Sciences 10.2 (2020): 666.

[19] Kamitani, Kojiro, et al. "Spinal posture in the sagittal plane is associated with future dependence in activities of daily living: a community-based cohort study of older adults in Japan." Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences 68.7 (2013): 869-875.

[20] Kanokros, K. (1987). *Exercise routines and optimal schedules.* Bangkok: Fitness and Health Publications, p. 325.

[21] Kao PC, Ferris DP. The effect of movement frequency on interlimb coupling during recumbent stepping. Motor Control 2005;9(2):144–63.

[22] Kawashima N, Nozaki D, Abe MO, Nakazawa K. Shaping appropriate locomotive motor output through interlimb neural pathway within spinal cord in humans. J Neurophysiol 2008;99(6):2946–55.

[23] Kornkan, S. (1995). *Principles of exercise program development.* Bangkok: Sport Science Publication, 19-24.

[24] Nongpimol Nimit-arnun, The innovation: Application of 9 square-stepping exercise program with Thai folk dance for fall prevention among community-dwelling older persons, Nursing Collage, Christian University of Thailand, Nakhon Pathom Province Office of the National Economic and Social Development Council,2021 44

[25] Report summary of illnesses, Health digital group, Strategy and Planning Division , Ministry of Public Health,2019 45

[26] Rockhill, B.; Willett, W.C.; Manson, J.E.; Leitzmann, M.F.; Stampfer, M.J.; Hunter, D.J.; Colditz, G.A. Physical activity and mortality: A prospective study among women. Am. J. Public Health 2001, 91, 578–583. [PubMed]

[27] Sandvik, L.; Erikssen, J.; Thaulow, E.; Erikssen, G.; Mundal, R.; Rodahl, K. Physical fitness as a predictor of mortality among healthy, middle-aged Norwegian men. N. Engl. J. Med. 1993, 328, 533–537.

[28] Suchner, D.M. 1997. Physical Activity and Quality of Life in Older Adults. The Journal of the American Medical Association South East Asia. 277(1): 64-66.

[29] Sedaghati, Parisa, Somayeh Ahmadabadi, and Maryam Goudarzian. "Evaluation of the durable effects of corrective exercises on the postural alignment and stability in hyperkyphotic elderly with a history of falls." BMC geriatrics 22.1 (2022): 545.

[30] Simpson, G. L. (1986). *Comprehensive fitness and health management.* New York: Wellness Publications.

[31] Suwan P, Kanthanaphat N, Soawaphan J, Intarasongkor S, Uonkeaw A, Hankla S. The development of practice guideline for preventing fall using 10 P's multifactorial concepts among older adults in community. Royal Thai Navy Medical Journal 2020;47(2):414-31. (in Thai).

[32] Swinnen SP. Intermanual coordination: from behavioural principles to neural-network interactions. Nat Rev Neurosci 2002;3(5):348–59.

[33] Voukelatos A, Cumming RG, Lord SR et al. A randomized, controlled trial of tai chi for the prevention of falls: The Central Sydney Tai Chi Trial. J Am Geriatr Soc 2007;55:1185–1191.

[34] Vidal, J.; Borràs, P.A.; Ponseti, F.J.; Cantallops, J.; Ortega, F.B.; Palou, P. Effects of a postural education program on school backpack habits related to low back pain in children. Eur. Spine J. 2013, 22, 782–787.

[35] Wannier T, Bastiaanse C, Colombo G, Dietz V. Arm to leg coordination in humans during walking, creeping and swimming activities. Exp Brain Res 2001;141(3):375–9.

[36] Wirun, C. (1994). *Endurance training and health benefits.* Bangkok: Health Promotion Press, p. 46.
[37] Woodard, C.; Berry, M. Enhancing adherence to prescribed exercise: Structured behavioral interventions in clinical exercise programs. J. Cardiopulm. Rehabil. 2001, 21, 201–209.
[38] Zehr EP, Duysens J. Regulation of arm and leg movement during human locomotion. Neuroscientist 2004;10(4):347–61.
[39] W. H. Organization, "Everybody's business: strengthening health systems to improve health outcomes: WHO's framework for action. Geneva," 2007.

