

## Article

# MUS3E: A Mobility Ubiquitous Sensor Edge Environment for the Elderly

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**Abstract:** With the ageing of society, the number of households with older individuals or couples living alone is increasing. An “ageing-in-place” approach allows older adults to continue to live at home and receive help only when needed. However, this approach is insufficient for emergencies, such as falls, as well as for individuals with gradually deteriorating health conditions, such as frailty. Unexpected accidents significantly reduce the quality of life (QoL) of older adults. This paper proposes a new framework, the mobility ubiquitous sensor edge environment (MUS3E), to digitally transform ordinary houses to detect the movement of older individuals throughout their home environment and to notify family members and care providers of residents’ health status and safety information. The framework can be easily and inexpensively installed in any home, transforming an ordinary house into a smart home with an automated function for monitoring older residents. It uses ambient sensors such as passive infrared ray sensors to automatically measure health conditions by measuring factors such as walking speed. Residents need not interact with or control the system and can go about their daily lives. Since the sensors used in this system are mass-produced consumer products, they are inexpensive and easily replaceable, as there are many alternatives. In this study, we were able to demonstrate the practicality and feasibility of this framework using a prototype that uses open architecture Internet of Things (IoT) software (Debian GNU/Linux 11, Arduino 1.8.19, ESP8266 2.7.4, ESP32 1.0.6, PubSubClient 2.8.0, ESPPerfectTime 0.3.0, mosquito 2.0.11) components to digitally transform the living environment of older individuals.



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**Keywords:** passive infrared ray (PIR) sensor; ultrasonic ranging sensor; walking speed; frailty; ubiquitous sensor networks

## 1. Introduction

Ageing populations represent a global concern. Moreover, the percentage of individuals aged sixty-five and over among the total global population is projected to increase [1,2]. As the proportion of older adults increases, a growing number of individuals will require nursing care. This will have a serious impact on social security costs, including the cost of health care and long-term care. When older adults require nursing care, their quality of life (QoL) may decline because they are no longer able to live independently. In addition, as birth rates are also declining in many countries worldwide, the burden of social security costs is resting on the shoulders of fewer workers.

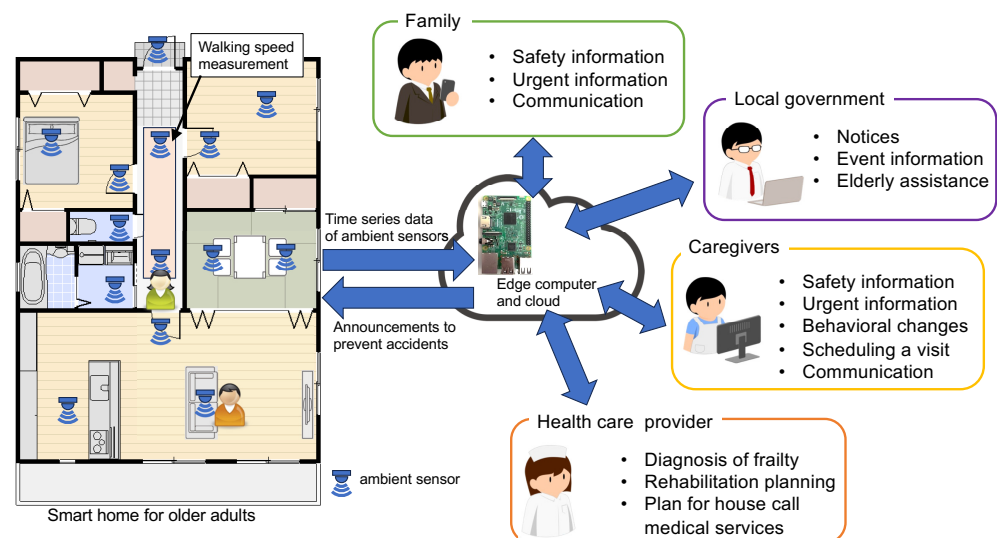
One solution to the problem of an ageing society is to extend the healthy life expectancy of older adults. This can reduce the cost of both health care and long-term care, while healthy older individuals can continue to contribute to society for longer, and thus reduce the financial burden on younger workers. Furthermore, healthy older adults can maintain their own QoL and continue to live independently.

The number of households comprising only older adults is also increasing, as many grown children have to move far away from their ageing parents to find work. Older adults in retirement homes and have no family nearby often become isolated from their

local communities and do not receive emotional support from family or friends. This can often have negative impacts on their mental health [3]. The “ageing-in-place” approach, which focuses on helping older individuals to remain living at home and to only receive assistance when needed, can alleviate these issues [4].

However, there are several challenges associated with the implementation of ageing in place. One is that emergencies, such as falls or heat stroke, may not be detected immediately in older adults who live independently. In addition, driving typically becomes more difficult with age, while a lack of public transportation, especially in rural areas, can make it difficult for older adults to access public medical and long-term care services. Furthermore, the early detection of frailty, a condition that occurs between health and ill health necessitating nursing care, can prove difficult in older adults who live independently. Frailty progresses gradually on a day-by-day basis, making it difficult to notice the signs. These challenges can significantly reduce the QoL of older adults [5].

In light of the above, the present paper proposes a digital transformation framework for older adults that can support ageing in place and extend their healthy life expectancy using Internet of Things (IoT) technology. Previous studies have proposed a method that can automatically and continuously measure the indoor walking speed of older adults using a passive infrared ray (PIR) sensor, i.e., a non-contact human-detection sensor, to detect signs of frailty in older adults at an early stage [6]. Building on such research, the present paper proposes a digital transformation (DX) framework for smart houses known as the mobility ubiquitous sensor edge environment for the elderly (MUS3E). This framework utilizes IoT technology based on open architecture software (Debian GNU/Linux 11, Arduino 1.8.19, ESP8266 2.7.4, ESP32 1.0.6, PubSubClient 2.8.0, ESPPerfectTime 0.3.0, mosquitto 2.0.11) components. Figure 1 illustrates a concept for a smart house for older residents using the MUS3E DX framework.



**Figure 1.** Smart house for older adults based on MUS3E, enabling communication among motion sensors, relatives and caregivers, and ambient sensor networks.

Jo et al. evaluated older adults’ perceptions of IoT-integrated smart home systems [5]. They found that the older adult participants expressed negative opinions regarding the usability, complexity, and inconvenience of such systems in relation to daily activities. The MUS3E uses ambient sensors such as motion sensors (i.e., PIR sensors), meaning the system does not require older adults to wear sensor devices or handle complex equipment. Instead, the data are collected as residents go about their normal daily activities. The detected data are saved to edge computers and cloud services, and the data are also provided to the relatives and caregivers who monitor the residents’ health conditions. As each ambient sensor is time-synchronized with a network time protocol (NTP) server, various data can be collected, including the residents’ walking speed, activity level, and indoor

activity patterns. Moreover, the system allows family members to access older adults' safety and emergency information, thereby enabling the speedier detection of anomalies such as reduced movement so that family members can take action quickly. The system can also help local government agencies monitor the health conditions of older adults and provide support as needed. Caregivers need access to older adults' safety and emergency information as well, and the system can help them schedule visits more efficiently and better respond to changes in older adults' behavioural patterns. In addition, the system can help health care providers diagnose frailty based on walking speed and physical activity data, while the stored data can also be used to more efficiently plan rehabilitation and house calls. The MUS3E system can alert older adults to environmental risks too, such as notifying residents about the risk of heat shock if there is a temperature difference between rooms. Furthermore, the MUS3E uses inexpensive, mass-produced sensors, which is important because it allows smart home systems to be built for a reasonable price and the sensors can be easily replaced if required.

In this paper, we implement and evaluate the feasibility of the MUS3E's basic functions, including the non-intrusive measurement of residents' walking speed and height. To accomplish this, the remainder of the paper is structured as follows. Section 2 discusses previous studies concerning the non-intrusive measurement of older adults' walking speed and height. Section 3 outlines the design of the MUS3E, including the walking speed measurements and system requirements. Section 4 details the sensors used in the MUS3E system and discusses their feasibility. Section 5 reports the walking speed measurement experiment that was conducted using a prototype of the MUS3E system. Section 6 discusses the findings, while Section 7 concludes the paper.

## 2. Related Work

This section discusses the findings of prior research concerning non-intrusive and non-wearable measurements of subjects' walking speed and height.

### 2.1. Non-Intrusive Walking Speed Measurement

Due to its simplicity and ease of access, the most basic method for the non-intrusive measurement of an individual's walking speed is the use of a stopwatch [7]. Yet, using a stopwatch requires another person to measure the time, which renders it an unsuitable method for long-term continuous measurement in a residential setting.

The automatic method of measuring an individual's walking speed is based on a timing gate method that uses a laser and a receptor to record the crossing times of two or more units [8–10]. The timing gate method requires the installation of gates, which can be an obstacles in narrow areas such as corridors. The walking speed measurement method proposed in this paper is also based on the timing gate method, although the utilized sensor is a PIR sensor, which is installed on the ceiling so that it does not interfere with walking even in narrow corridors. Furthermore, by installing the sensor on the ceiling of a room, it is possible to detect the movement of older adults indoors as well as their walking speed.

Windham et al. used electronic mats to measure individual's walking speed and walking patterns [11], while Caliskanelli et al. proposed a method for assessing frailty based on walking speed measurements and a gait analysis using the Kinect, a three-dimensional (3D) depth camera developed by Microsoft Co., Ltd. [12]. These methods can both perform a gait analysis as well as gait speed measurements, allowing for the detailed examination of an individual's health status. Still, while these methods are effective in large places, such as examination sites, they are not suitable for continuous automatic measurement in the homes of the older adults because the utilized device is large and requires an operator.

### 2.2. Non-Intrusive Height Measurement

Non-intrusive methods for measuring height have been proposed for over 20 years. For example, BenAbdelkader et al. presented a parametric method for automatically

identifying individuals in monocular low-resolution videos via estimating their height and the stride parameters of their gait [13].

Srinivasan et al. evaluated the use of height for the biometric identification of residents by mounting ultrasonic ranging sensors above the doorways in a home [14]. In so doing, they showed that height sensors can potentially achieve at least 95% identification accuracy in 95% of older adults' homes in the United States. Moreover, the use of commercially available sensors made it possible to realize a low-cost system. However, the use of dedicated interfaces for data communication limited the scalability of the system.

In this paper, the cost of the MUS3E system is reduced by using ultrasonic sensors that are mass-produced for consumer use. Additionally, the sensor network was built using Wi-Fi, a standard approach, making the MUS3E system scalable.

### 3. Design of the MUS3E System

This section describes the design of the MUS3E system. In so doing, it elucidates the walking speed measurement approach and the system requirements.

#### 3.1. Measuring Walking Speed during Daily Activities

Various approaches have been proposed to monitor the activity levels of older adults in their homes. One such approach involves the use of an inertial measurement unit (IMU) device, such as a smartwatch or smartphone, equipped with an accelerometer and angular velocity sensor. The data collected using this device are then analysed to assess the subject's gait [15–19]. Another approach utilizes Bluetooth low-energy (BLE) beacons to measure changes in individuals' indoor activity and behaviour [20–22]. With this method, the BLE beacons are strategically placed around the house, and the resident wears a BLE receiver. Wearable sensors can accurately measure vital signs, including an individual's heart rate and body temperature. However, older adults often find wearable sensors burdensome, and they may refuse or forget to wear them [5]. As a consequence, while wearable sensors are highly effective for short-term measurement purposes, their use for long-term continuous measurement purposes is challenging.

The MUS3E employs non-wearable and non-intrusive sensors to facilitate long-term continuous measurements. Thus, older adults can monitor their activities simply by going about their daily routines without being conscious of the system's presence, resulting in an extremely low burden. In this paper, we implemented the basic functionality of the MUS3E system. More specifically, we implemented the walking speed measurement function of the system using a PIR sensor and the individual identification method using an ultrasonic ranging sensor, allowing us to evaluate the feasibility of the MUS3E system.

Walking speed is a valid, reliable, and sensitive measure for both assessing and monitoring functional status, leading to its recognition as the "sixth vital sign" [23]. Walking speed is also evaluated during frailty checkups for older adults [24]. As such, it is crucial to continuously measure the indoor walking speed of older adults in order to detect any changes as soon as possible. Additionally, the MUS3E system identifies individuals by measuring their height using an ultrasonic ranging sensor simultaneously with the measurement of their walking speed. This is necessary to distinguish the walking speed of each resident in a households with multiple occupants, such as a household comprising an elderly couple.

Ambient sensors, such as PIR and an ultrasonic ranging sensors, are mass-produced consumer products that are readily available, inexpensive, and non-wearable. These ambient sensors reduce the burden on older adults and can be used to construct a low-cost system that is easily installable in the home environment. As a result, the MUS3E system can continuously and automatically measure the walking speed of each older adult in the house while they go about their daily routines.

#### 3.2. Design of the MUS3E System

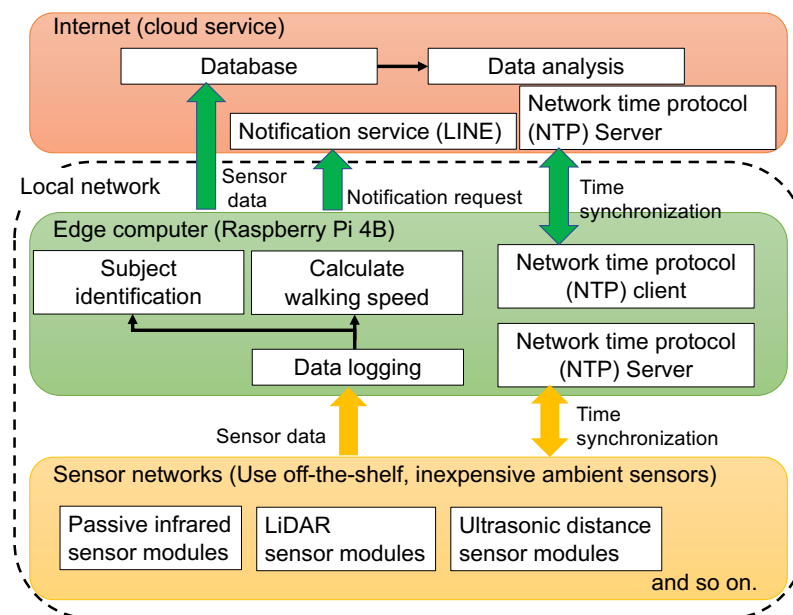
Table 1 shows the items required for the MUS3E system.

**Table 1.** Required items for the MUS3E system.

Item	Description
Privacy	Avoid sensors that are a significant invasion of privacy, such as video cameras.
Burden	Do not require older adults to perform complicated operations.
Cost	Use devices and sensors that are mass-produced consumer products.
Sustainability	Use off-the-shelf sensors that can easily be replaced because there are many alternatives.
Multifunctionality	Beneficiaries include not only older adults, but also their families, caregivers and other medical professionals.

Video cameras offer a convenient monitoring method. However, due to privacy concerns, many older adults are reluctant to install a camera system that would allow people other than their family members to watch them [25]. Reducing the burden on older adults is also an important factor. The use of wearable sensors requires older adults to change the sensor and send data from the wearable sensor to a smartphone via Bluetooth. Furthermore, wearing a sensor twenty-four hours a day could pose a significant burden for older adults. Therefore, the system developed in the present study uses non-wearable ambient sensors so that data are collected as older adults go about their daily lives. Cost is also an important factor. Therefore, the sensors and devices used in this study are mass-produced and inexpensive; this reduces the cost of the system and facilitates system deployment. Finally, the system should be sustainable. It is difficult to continue using existing products when a company fails or when specially designed sensors break. Therefore, our framework uses mass-produced, off-the-shelf products for which there are many alternatives to ensure that the system can be used long-term. The system is also multifunctional, with the proposed framework not only supporting the health care of older adults and prevent emergencies, but also helping families confirm the safety of older relatives, help care providers work more efficiently, and support more efficient use of telemedicine and home visits by medical personnel.

Figure 2 shows the logical architecture of the MUS3E.



**Figure 2.** Logical architecture of the MUS3E system. The MUS3E system consists of three layers: sensor networks, edge computers, and the Internet (cloud services). Even without internet access, the system can measure walking speed over a local network.



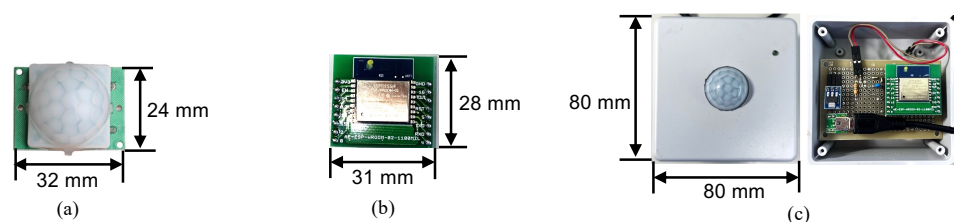
At the sensor networks layer, a message-queueing telemetry transport (MQTT) protocol is used to allow sensors to communicate with edge computers. This approach is highly scalable and can be expanded to include more sensors. Our prototype uses PIR, a light detection and ranging (LiDAR), and ultrasonic ranging sensors. When measuring walking speed, the time of detection is important, and all sensors must be synchronized. Therefore, each sensor synchronizes its time with the NTP server of the edge computer or that of the Internet.

The edge computer layer collects data from the sensors, calculates the walking speed, and stores the sensor data. If an internet environment is available, sensor data can be aggregated into a database for big data analysis, and social network services (SNS) such as LINE, popular application in Japan, can be used to provide added value, such as sending notifications to family members or caregivers. The sensors can also be synchronized with an external NTP server to ensure accurate timekeeping. If there is no internet access, basic functions such as walking speed measurements will still work within a local network, but SNS notification will not be available. To minimize errors, the edge computer is synchronized with a real-time clock module. When relatives and caregivers make regular visits, they can use their smartphones to provide a temporary internet connection. Edge computers and real-time clock modules can use the temporary internet access to correct the time and send data to appropriate individuals.

#### 4. System Configuration of the MUS3E System

##### 4.1. Sensor Modules

Figure 3 shows a PIR sensor module. This module measures walking speed by measuring the time a subject takes to move from one PIR sensor module to another.



**Figure 3.** Configuration of the PIR sensor module. (a) PIR sensor, Nanyang Senba Optial and Electronic Co., Ltd. SB612. (b) Wi-Fi microchip, Akizuki Denshi Tusho Ltd. ESP-WROOM-02 pitch conversion kit (ESP8266), (c) Composed of (a,b). (“mm” stands for “millimetres”).

The PIR sensor module (Figure 3c) consists of a PIR sensor (Figure 3a) and an ESP-WROOM-02 (ESP8266) Wi-Fi microcontroller module (Figure 3b). The PIR sensor has a detection angle of  $115^\circ$  and a detection depth range of 8 m. The ESP-WROOM-02 is equipped with an ESP8266 chip from Espressif Systems [26] and has Wi-Fi communication and microcontroller functions.

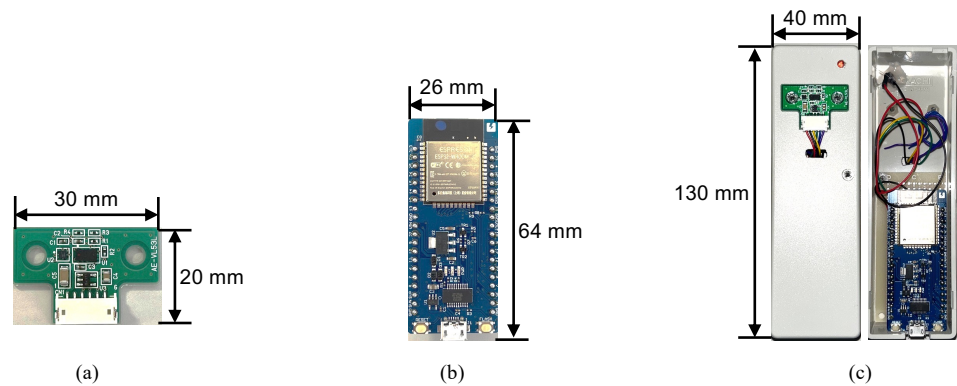
Delays in communication between the sensor module and the edge computer or in processing by the edge computer can affect the accuracy of the walking speed measurements. To avoid such delays, the sensor modules synchronize with the NTP server on the Internet. If there is no internet access, the sensor modules synchronize with the NTP server on the edge computer. Using an ESPPerfectTime library [27], the ESP-WROOM-02 can synchronize its time with the NTP server. This library also accounts for the round-trip time (RTT) with the NTP server, enabling highly accurate time synchronization.

The ESP-WROOM-02 records the time when the PIR sensor detects the subject and sends it to the edge computer via Wi-Fi. The time data are sent in the javascript object notation (JSON) format shown in Figure 4.

```
{“ID”: sensor ID, “Year”: year, “Month”: month, “Day”: day, “Hour”: hour,
“Min”: minute, “Sec”: second, “USec”: micro seconds}
```

**Figure 4.** Format of data sent from the PIR sensor modules to the edge computer.

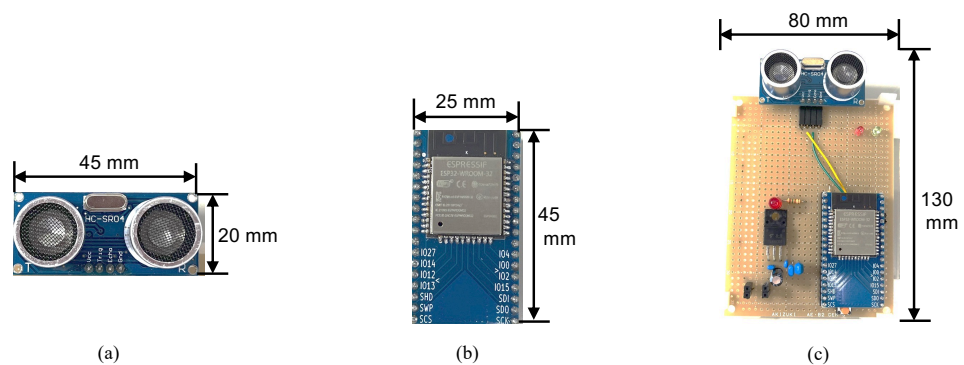
Figure 5 shows a LiDAR sensor module. This module is used to verify the accuracy of the walking speed measurement performed using the PIR sensor modules, and can be used in conjunction with the PIR sensor modules.



**Figure 5.** Configuration of the LiDAR sensor module. (a) LiDAR sensor, Akizuki Denshi Tsusho Ltd. AE-VL53L0X. (b) Wi-Fi microchip, SWITCH SCIENCE ESPr Developer 32 (ESP32). (c) Composed of (a,b) (“mm” stands for “millimetres”).

The LiDAR sensor module (Figure 5c) consists of a LiDAR sensor (Figure 5a) and an ESPr Developer 32 (ESP32) microcontroller module (Figure 5b). The LiDAR sensor module can measure distances of up to 2 m using a 940 nanometres class-one laser. The ESPr Developer 32 is equipped with the ESP32 chip from Espressif Systems [26] and has Wi-Fi and BLE communication and microcontroller functions. Like the ESP-WROOM-02, the ESPr Developer 32 uses ESPPerfectTime [27] to synchronize its time with the edge computer or the online NTP server. When the subject passes in front of the LiDAR sensor module, the module sends the detection time. These data are sent in the same format as those detected by the PIR sensor (Figure 4). Walking speed is measured as the time it takes the subject to move from one LiDAR sensor module to another.

Figure 6 shows an ultrasonic ranging sensor module. This module is installed on the ceiling and is used to estimate the height of a subject who passes underneath it.



**Figure 6.** Configuration of the ultrasonic ranging sensor module. (a) Ultrasonic ranging sensor, Rainbow E-Technology Co., Ltd. HC-SR04. (b) ESP32-WROOM-32, (c) Composed of (a,b) (“mm” stands for “millimetres”).

As shown in Figure 6c, the ultrasonic ranging sensor module consists of an ultrasonic ranging sensor (HC-SR-04) (Figure 6a) and an ESP32-WROOM-32 microcontroller module (Figure 6b). The detection angle of the ultrasonic ranging sensor is  $15^\circ$ , and its measurement range is from 2 to 400 cm. The ESP32-WROOM-32 microcontroller uses the chip shown in Figure 5b, but it is a less expensive module. When the PIR sensor detects the subject,

distance measurement begins, and the subject's height is calculated using the distance to the subject ( $d_{sub}$ ) and the floor ( $d_{max}$ ).

$$height = d_{max} - d_{sub} \quad (1)$$

#### 4.2. Edge Computer in the MUS3E

A Raspberry Pi 4B is the edge computer in our prototype. In the edge computer, Mosquitto, an open-source MQTT broker software (mosquitto 2.0.11), is used to collect data from the sensor modules and calculate the walking speed  $W_s$ .

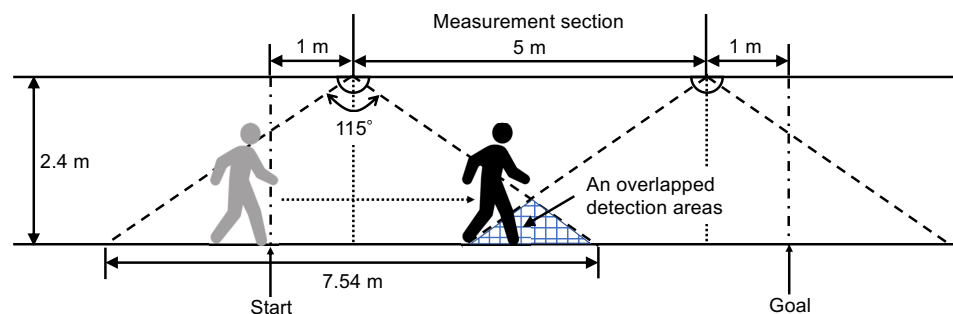
$$W_s = \frac{distance(PIR_1, PIR_2)}{|t_{PIR_1} - t_{PIR_2}|} \quad (2)$$

In this equation,  $distance(PIR_1, PIR_2)$  is the known distance between  $PIR_1$  and  $PIR_2$ ,  $t_{PIR_1}$  is the time of detection by  $PIR_1$ , and  $t_{PIR_2}$  is the time of detection by  $PIR_2$ . When internet access is available, a relay program on the edge computer sends these data to another online MQTT broker, and the time is synchronized with an online NTP server. LINE is used to notify family and caregivers about the subject's condition. A notification program that uses LINE can be created in Python using the LINE notify application programming interface (API).

When internet access is not available, the edge computer synchronizes its time with a real-time clock module and logs walking speed data. The time of the sensor module is synchronized with that of the edge computer, thus not interfering with the walking speed measurement. When family members or caregivers come to the subject's home, they can use a smartphone to provide temporary internet access, retrieve data, and resynchronize the time. When cell phone reception is poor, data can be collected directly from the edge computer.

#### 4.3. Limitations of the Detection Range of the PIR Sensors

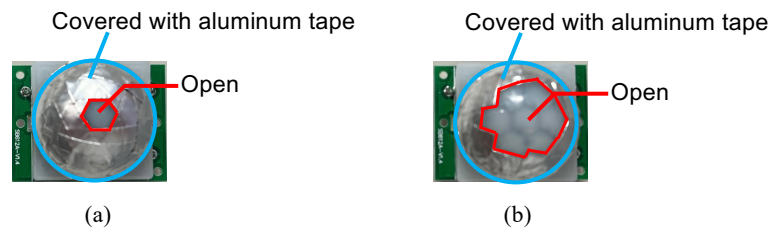
In conventional measurements of walking speed during frailty checks, the subject starts walking one metre before the measurement start position and continuous walking one metre past the measurement end position. The subject's speed is measured for five metres. As shown in Figure 7, the detection angle of the PIR sensor is  $115^\circ$ , and its detection range is about 7.54 m in a corridor with a height of 2.4 m. Thus, the detection areas of the two PIR sensors overlap. As a result, as shown in Figure 7, the PIR sensor already detects at the start point, and another PIR sensor detects at the overlap point, detecting at a distance shorter than five metres. Thus, accurate walking speed cannot be measured.



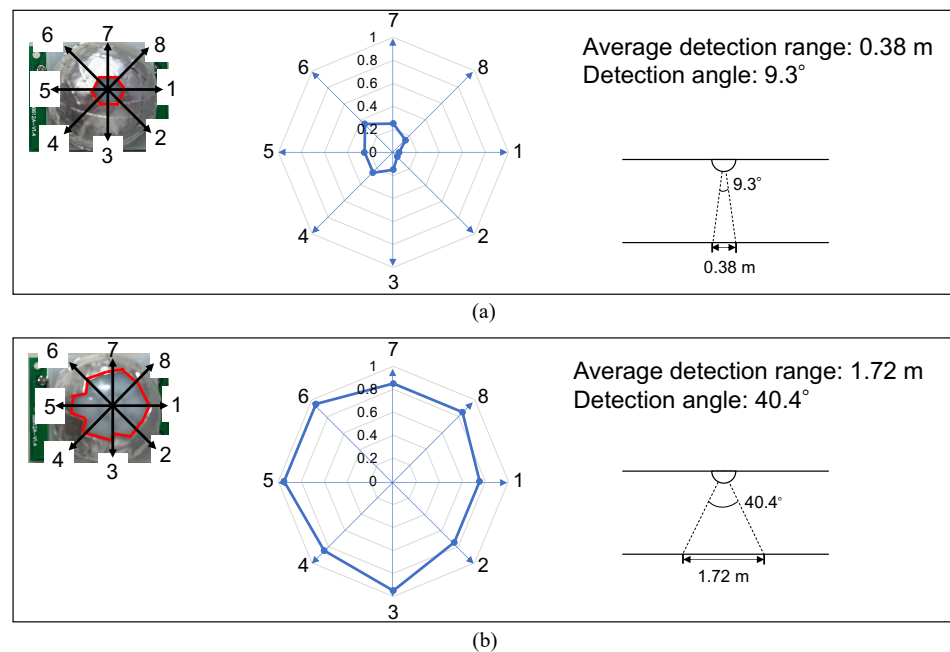
**Figure 7.** Coverage and overlap of the PIR sensor detection ranges. (“m” stands for “metres”).

To limit the detection ranges of the PIR sensor, two types of covers were made with aluminium tape, which infrared rays cannot pass through. As shown in Figure 8, one covers all but one of the Fresnel lens, and the other leaves the centre and periphery uncovered. The measured detection area for each cover is shown in Figure 9.





**Figure 8.** Two types of masks to limit the detection ranges of the PIR sensors. (a) Cover all but one lens with aluminum tape. (b) Cover with aluminum tape, except in the center and around the perimeter.



**Figure 9.** Detection ranges of the PIR sensors with the two types of masks. (a) Detection area with cover in Figure 9a. (b) Detection area with cover in Figure 9b. (“m” stands for “metres”).

In Figure 9a, the detection range of the PIR sensor is almost directly below the sensor. Since the detected location can be measured accurately, the walking speed can be measured very accurately. In narrow places such as corridors, the PIR sensor shown in Figure 9a can be used to measure walking speed with high accuracy. In Figure 9b, the detection area is wider than in Figure 9a, so the accuracy of the walking speed measurement is slightly lower. However, when measuring walking speed over a large area, such as a room, the sensor placements illustrated in Figure 9b offer a trade-off between accuracy and cost because this system can cover a larger area with fewer sensors.

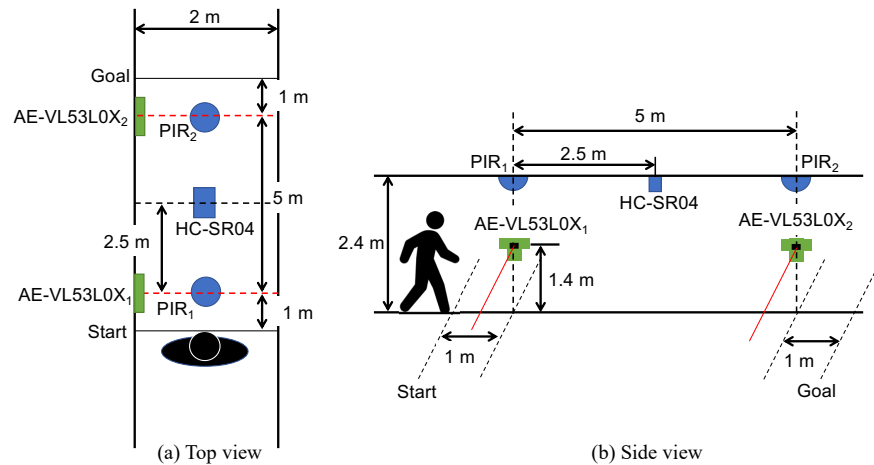
Finally, Table 2 shows the price of the sensors and edge computer used in this study. All sensor modules and edge computers shown in Table 2 are inexpensive, readily available consumer products.

**Table 2.** Retail price of the sensor modules and edge computer (as of June 2023).

Sensor Modules	Retail Price (US Dollars)
PIR sensor (Motion sensor)	4.4
ESP-WROOM-02 pitch conversion kit (Wi-Fi microcontroller)	4.3
AE-VL53L0X (LiDAR)	7.9
ESP8266 Developer 32 (Wi-Fi + BLE microcontroller)	16.2
HC-SR04 (Ultrasonic ranging sensor)	2.2
ESP32-WROOM-32 (Wi-Fi + BLE microcontroller)	7.3
Raspberry Pi 4 B (Edge computer)	106.9

## 5. Demonstration and Experiments with the MUS3E Prototype

To study the feasibility and effectiveness of the MUS3E system in the homes of older adults, we used a prototype to measure walking speed, one factor used in the early detection of frailty. Because corridors are often used as a flow line for older adults to access rooms or leave the house, walking speed was measured in the corridor. Figure 10 shows the placement of the individual sensor modules for a measurement distance of five metres. The HC-SR04 ultrasonic ranging sensor was installed in the ceiling between  $PIR_1$  and  $PIR_2$  to test whether individuals could be identified based on their physical characteristics such as height and posture.



**Figure 10.** Placement of sensors in the experiment to measure walking speed. (“m” stands for “metres”).

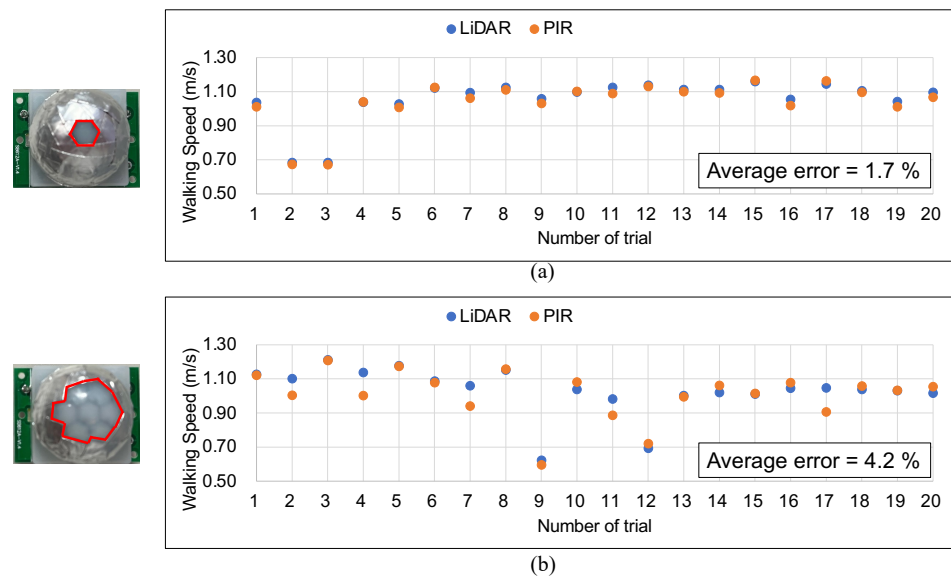
In the experiment, the subject walked from one metre before the measurement section to one metre after the measurement section. The subject walked back and forth ten times.  $PIR_1$ ,  $PIR_2$ , and LiDAR (AE-VL53L0X<sub>1</sub>, AE-VL53L0X<sub>2</sub>) sent the time when the subject passed the sensor to the edge computer. When the PIR sensor detected the subject, it sent a trigger to the HC-SR04 ultrasonic ranging sensor, which continuously measured the distance for ten seconds to obtain information about the subject’s height.

### 5.1. Walking Speed Measurement: Distance between PIR Sensors and Measurement Accuracy

In a conventional frailty diagnosis, walking speed is measured for a distance of five metres. Therefore, for this distance, the PIR and LiDAR sensors were used to simultaneously measure walking speed, as shown in Figure 10, to confirm the accuracy of the PIR sensors’ measurements.

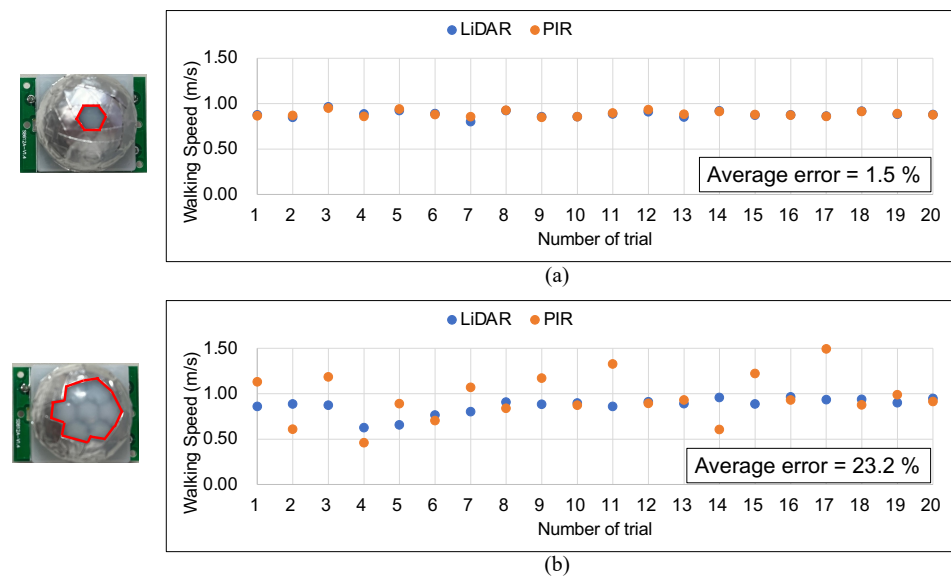
As Figure 11a shows, over a distance of five metres, the PIR sensors’ measurements were highly accurate, with an average error rate of 1.7%. In Figure 11b, similar measurements were made with a mask with a wider detection range than the mask in Figure 11a. As a result, although the subject detection point contained errors due to the wider detection range, the measurement section was five metres wide compared to the detection range of 1.72 m, so overlap of the detection range did not occur and measurements were made with high accuracy. Therefore, walking speed, a factor in conventional frailty diagnoses, could be continuously and automatically measured using ambient sensors such as PIR sensors with an MUS3E system.

Some homes may not have a five-metre-long corridor where walking speed can be measured. Therefore, we also checked whether walking speed could be accurately measured over a shorter distance. Since walking speed is measured for five metres during frailty diagnoses, a measurement taken over a shorter distance cannot support a medical diagnosis. However, continuous measurements can be used to track a decline in walking speed, which can indicate the need for a frailty checkup.



**Figure 11.** Comparison of the accuracy of walking speed measurements for a distance of five metres using LiDAR and PIR sensors. (a) Comparison of walking speed measurement between using PIR covered with Figure 9a and LiDAR. (b) Comparison of walking speed measurement between using PIR covered with Figure 9b and LiDAR. (“m/s” stands for “metres per second”).

The results of the walking speed measurements taken over a distance of one metre are shown in Figure 12.



**Figure 12.** Comparison of the accuracy of walking speed measurements using LiDAR and PIR sensors over a distance of one metre. (a) Comparison of walking speed measurement between using PIR covered with Figure 9a and LiDAR. (b) Comparison of walking speed measurement between using PIR covered with Figure 9b and LiDAR. (“m/s” stands for “metres per second”).

As shown in Figure 12a, walking speed could be measured with high accuracy over a distance of one metre, so the proposed framework can be used in homes where a five-metre-long measurement distance is not available. As shown in Figure 12b, the accuracy of walking speed detection is lower for this distance because the detection areas of the two sensors overlap when the measurement area is one metre, as shown in Figure 7.

### 5.2. Identifying Individuals Using PIR and Ultrasonic Ranging Sensors

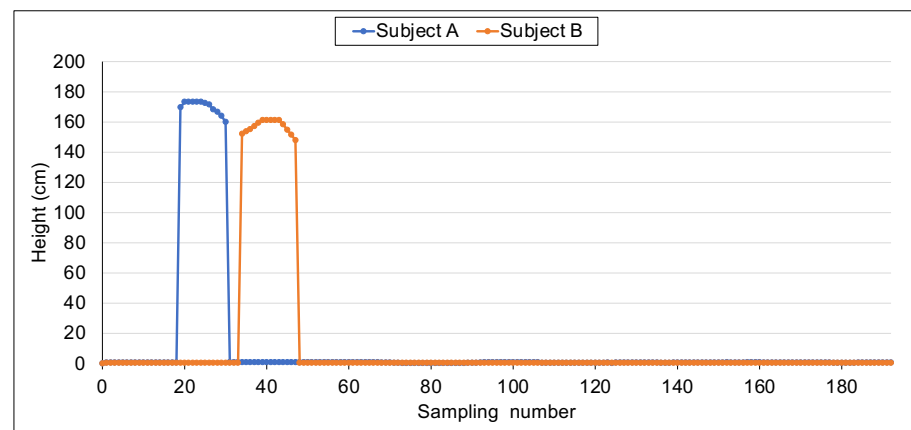
The PIR sensor cannot identify individuals because it detects infrared radiation emitted by a heat source. Thus, it cannot accommodate households with older couples who want to measure their respective walking speeds. Therefore, we next verified whether it is possible to measure the walking speeds of multiple subjects by measuring physical characteristics such as height and posture in the area where walking speed is measured.

The walking speeds of subjects A and B, who have different heights, were measured. To measure height, an ultrasonic ranging sensor was placed in the middle of the measurement section. The heights of the subjects and their measured walking speeds are shown in Table 3.

**Table 3.** Heights and walking speeds of the subjects in the prototype experiment.

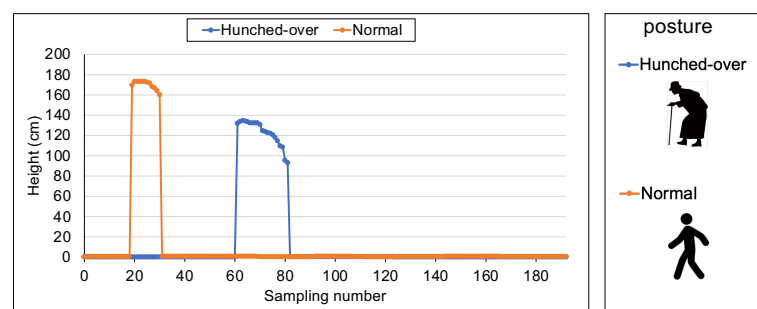
	Height (cm)	Walking Speed (m per s)
Subject A	180	1.24
Subject B	165	1.03

Figure 13 shows the height data for subjects A and B collected by the ultrasonic ranging sensor. These values are lower than the subjects’ actual heights because walking height is lower than standing height. The median value of nine measurements was used to eliminate noise. The walking speed measurements of subjects who have different heights can be distinguished based on the height data.



**Figure 13.** Subjects’ height measurements by ultrasonic ranging sensors. (“cm” stands for “centimetres”).

Figure 14 shows the height measurements for one subject walking with a normal posture and with a hunched-over posture, as is common in older adults. Since the waveform differs based on posture, it seems possible to identify individuals based on height.



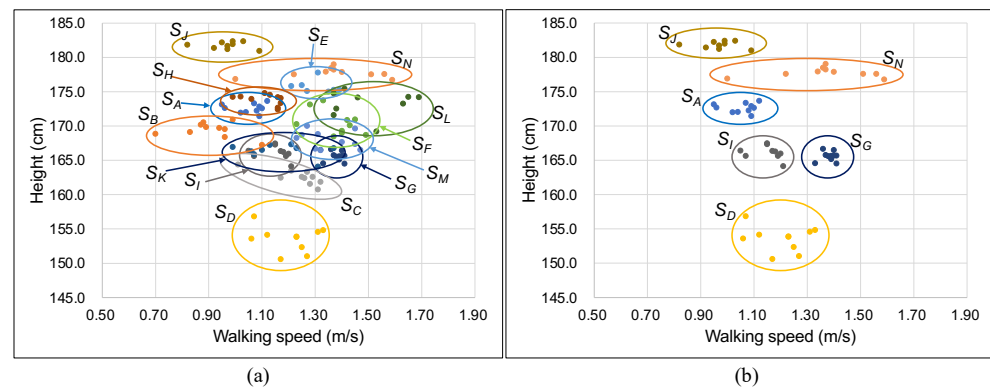
**Figure 14.** Height measured by an ultrasonic ranging sensor for a normal and a hunched-over posture. (“cm” stands for “centimetres”).

Next, we measured multiple subjects to determine if it was possible to discriminate between them. First, we measured the actual height of the 14 subjects. Then we measured their walking speed and height by making five round trips over the measurement section. Table 4 shows each subject’s actual height and average walking speed for five round trips.

**Table 4.** The measured height and average walking speed of the 14 subjects.

Subject	Height (Actual) (cm)	Average Walking Speed (m/s)	Subject	Height (Actual) (cm)	Average Walking Speed (m/s)
A	174	1.05	H	175	1.11
B	165	1.03	I	166	1.15
C	164	1.24	J	180	0.97
D	160	1.20	K	168	1.18
E	176	1.32	L	176	1.50
F	175	1.38	M	171	1.35
G	166	1.38	N	180	1.37

The measurement results are presented in Figure 15a. It can be observed that identification is possible when there is a clear difference in height, as in the case of subject D ( $S_D$ ) and  $S_J$ . (“cm” and “m/s” stand for “centimetres” and “metres per second”, respectively.)



**Figure 15.** (a) Results of walking speed and height measurements for multiple subjects. (b) An example of clustering based on  $S_A$ , dependent on a difference between height and walking speed. (“cm” and “m/s” stand for “centimetres” and “metres per second”, respectively).

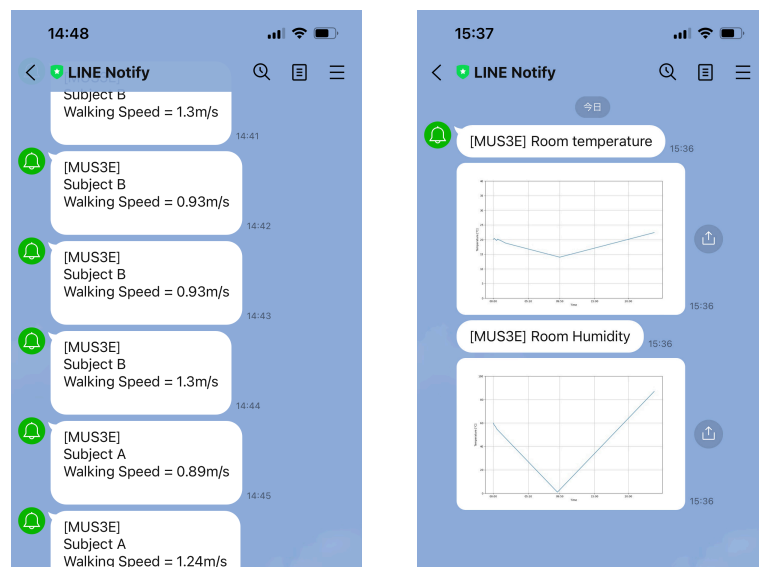
By taking subject  $S_A$  (height = 174 cm) as a reference and selecting subjects with a height difference of 5 centimetres or more (height  $\leq 169$  cm and height  $\geq 179$  cm), we find that subjects  $S_C, S_D, S_G, S_I, S_J, S_K$  and  $S_N$  fall into this category. Since subjects  $S_C, S_G, S_I$  and  $S_K$  overlap in this category, we further select subjects  $S_I$  and  $S_G$  by choosing those with an average walking speed difference of 0.2 m per second or more. These selections are illustrated in Figure 15b. While it is not possible to distinguish all 14 subjects, it can be observed that they can be differentiated based on differences in their height and walking speed. Thus, it is possible to identify and measure individuals in households of elderly couples when there is a difference in height or walking speed.

### 5.3. Notifications

Notifications from the MUS3E system can provide important information to family members, caregivers, and others who support older adults. Notifications can be sent by e-mail, but recipients may receive a variety of other e-mails in addition to those from the MUS3E system, which may delay responses to important e-mails. Therefore, in this study, we confirmed the feasibility of a notification method using LINE, a popular SNS application in Japan. LINE allows individuals and groups to exchange messages and pictures and can be used to send notifications to family members, caregivers, and medical personnel.



Here, we confirmed that LINE can notify a user of an older adult's walking speed and environmental information such as temperature and humidity. Figure 16 shows some of these notifications. Since LINE can send images as well as text, it is also possible to generate and send images that visualize data in the form of graphs.



**Figure 16.** SNS notifications from the MUS3E system.

## 6. Discussion

This paper introduced the MUS3E system as a DX platform for smart homes for older adults. The MUS3E system uses mass-produced, low-cost sensors, such as PIR sensors, making it possible to build a low-cost system and a sustainable framework with many alternatives. Moreover, wireless technology obviates the need for extensive renovation work, and the MUS3E system can be easily installed in existing homes to facilitate DX. To monitor the well-being of older adults, the MUS3E system measures their walking speed, one of their activity indicators, using non-intrusive and non-wearable PIR sensors. This method of measurement is less burdensome for older adults and is suitable for long-term, continuous monitoring of activity levels.

The accuracy of the proposed walking speed measurement method was compared to the timing gate method using LiDAR sensors. The results indicated that the proposed method had equivalent accuracy to the timing gate method when the distance between two PIR sensors was set to five metres and one metre, respectively. As a result, the system could be installed in the homes of older adults where space is limited. In a previous study [5], older adult participants expressed negative opinions regarding the usability, complexity, and inconvenience of such systems in relation to daily activities. For example, measuring activity with a smartwatch required transmitting the measured data via BLE communication and retrieving the data, which had to be performed by the older adults themselves. Additionally, wearable sensors could be rejected or forgotten over time. By using ambient sensors, such as PIR sensors, MUS3E could greatly reduce the burden on older adults by measuring their activities, such as walking speed, and collecting data by simply going about their daily routines.

The proposed method could also be applied to monitor frailty in the home of older adults, building on the approach of a previous study that used wearable insole-type sensors to measure walking speed [28]. However, this approach was challenging to implement in cultures where it is customary to remove shoes indoors, such as in Japan. By incorporating the proposed method, the applicability of this approach could be broadened.

To address the limitation of PIR sensors in identifying individuals, a personal identification method that incorporated an ultrasonic ranging sensor was evaluated. The system was found to be capable of identifying individuals based on differences in height and

walking speed. As a result, it was possible to monitor the activities of each person even in a household with multiple occupants, such as an elderly couple's home.

By using LINE SNS services, family members and caregivers could directly receive notifications of important data in near real-time. In addition to text data, graphs and other data visualizations could be sent. This information could also serve as a tool to encourage communication by prompting related people to contact the elderly, thereby preventing them from becoming isolated in their community.

If there is no internet access, in the home, some features such as notifications are not possible, but necessary data, such as walking speed, could still be measured and stored on a local network. Data could then be collected and stored in the cloud via a smartphone network, or log data could be retrieved directly from the edge computer during caregiver visits.

One of the main aspirations of most older adults is ageing in place, that is, to remain in their own home independently, for as long as possible [4]. However, a major challenge to ageing in place is the lack of environmental monitoring. The MUS3E system can address this challenge by providing relevant information, such as health status and emergency alerts, to the appropriate parties, while allowing older adults to carry out their daily routines without being aware of the system. This can improve the QoL of older adults and extend their healthy life expectancy through early detection of health changes.

This study did not consider network security, which is a necessary element for practical applications. If important information, such as the activity patterns of older adults, were leaked to unrelated people, they could be targeted by in crimes such as robbery. Therefore, it will be necessary to combine network intrusion detection methods such as those presented in previous studies [29].

## 7. Conclusions

With the ageing of society, there is a growing trend of older individuals or couples living alone in their own households. The ageing-in-place approach is a desirable option for older adults who wish to stay at home and receive assistance only when necessary. However, this option poses risks for emergencies, such as falls, and for gradual decline, such as frailty. These unforeseen incident can severely affect the QoL of older adults. In this paper, we proposes a novel framework, the MUS3E system, digitally transforming ordinary homes into ubiquitous sensing environments that monitor the movements of older adults and to alert their family members and caregivers of their health and safety information.

The proposed framework can be easily and cost-effectively installed in an ordinary home after its residents have aged, transforming it into a smart home equipped with automated monitoring functions for older adults. The system employs ambient sensors, such as PIR sensors, to track health conditions such as frailty by measuring walking speed. Residents do not need to interact with the system and can carry on with their daily lives. As the sensors are mass-produced consumer products, they are affordable and can be easily replaced if necessary. In this study, we demonstrate the practicality and feasibility of our framework using a prototype based on open-architecture IoT software (Debian GNU/Linux 11, Arduino 1.8.19, ESP8266 2.7.4, ESP32 1.0.6, PubSubClient 2.8.0, ESPPerfectTime 0.3.0, mosquito 2.0.11) components.

We developed sensor modules and conducted walking speed measurement experiments, which demonstrated the high accuracy of our system in measuring walking speed. This confirms the practicality of our proposed method. Furthermore, since the MUS3E system can be easily connected to SNS, it serves as a useful monitoring system and provides a practical means of communication for connecting older adults with their family members and caregivers.

Concerning future work, we aim to install our system in large residential facilities for older adults, such as in nursing homes, to help reduce the workload of the staff. We also plan to investigate the applicability of our system to measuring people's movements in public spaces, such as shopping malls and universities. It is currently challenging to track

individual movements in crowded areas, and it may be beneficial to combine our approach with other methods such as BLE beacons.

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### Abbreviations

The following abbreviations are used in this manuscript:

QOL	Quality of life
IoT	Internet of Things
DX	Digital transformation
HEM	Home energy management
NTP	Network time protocol
IMU	Inertial measurement unit
MQTT	Message-queueing telemetry transport
LiDAR	Light detection and ranging
PIR	Passive infrared ray
SNS	Social network services
JSON	Javascript object notation
API	Application programming interface

### References

1. United Nations. *World Population Prospects 2022: Summary of Results*; UN: New York, NY, USA, 2022; pp. 7–9.
2. Annual Report on the Aging Society. Available online: <https://www8.cao.go.jp/kourei/whitepaper/index-w.html> (accessed on 6 May 2023).
3. Canjuga, I.; Želenznik, D.; Neuberg, M.; Božicevic, M.; Cikac, T. Does an impaired capacity for self-care impact the prevalence of social and emotional loneliness among elderly people? *Work Older People* **2018**, *22*, 211–223. [[CrossRef](#)]
4. Farber, N.; Shinkle, D. *Aging in Place: A State Survey of Livability Policies and Practices*; AARP Public Policy Institute: Washington, DC, USA, 2011.
5. Jo, T.H.; Ma, J.H.; Cha, S.H. Elderly Perception on the Internet of Things-Based Integrated Smart-Home System. *Sensors* **2021**, *21*, 1284. [[CrossRef](#)] [[PubMed](#)]
6. Utsumi, T.; Hashimoto, M. A Development of an Early Detection System of Pre-frailty in Senior Citizens Living Inside. In Proceedings of the International Conference on Ubiquitous Information Management and Communication (IMCOM2023), Suwon, Republic of Korea, 3–5 January 2023.
7. De la Cámara, M.Á.; Sara, H.-F.; Kabir, P.S.; Irene, E.-C.; David, M.-G.; Óscar, L.V. Clinical and Ambulatory Gait Speed in Older Adults: Associations with Several Physical, Mental, and Cognitive Health Outcomes. *Phys. Ther.* **2020**, *100*, 718–727. [[CrossRef](#)] [[PubMed](#)]
8. Jung, H.-W.; Roh, H.-C.; Kim, S.; Kim, S.; Kim, M.; Won, C.W. Cross-Comparisons of Gait Speeds by Automatic Sensors and a Stopwatch to Provide Converting Formula between Measuring Modalities. *Ann. Geriatr. Med. Res.* **2019**, *23*, 71–76. [[CrossRef](#)]
9. Kirmizi, M.; Simsek, I.E.; Elvan, A.; Akcali, O.; Angin, S. Gait speed and gait asymmetry in individuals with chronic idiopathic neck pain. *Musculoskelet. Sci. Pract.* **2019**, *41*, 23–27. [[CrossRef](#)] [[PubMed](#)]
10. Warden, S.J.; Kemp, A.C.; Liu, Z.; Moe, S.M. Tester and testing procedure influence clinically determined gait speed. *Gait Posture* **2019**, *74*, 83–86. [[CrossRef](#)] [[PubMed](#)]
11. Windham, B.G.; Griswold, M.E.; Ranadive, R.; Sullivan, K.J.; Mosley, T.H.; Mielke, M.M.; Jack, C.R., Jr.; Knopmen, D.; Petersen, R.; Vemuri, P. Relationships of Corebral Perfusion with Gait Speed Across Systolic Blood Pressure Levels and Age: A Cohort Study. *J. Gerontol. Med. Sci.* **2023**, *78*, 514–520. [[CrossRef](#)] [[PubMed](#)]

12. Caliskanelli, I.; Nefti-Meziani, S.; Hodgson, A. Kinecting Frailty: A Pilot Study on Frailty. In Proceedings of the International Conference on Human Aspects of IT for the Aged Population, Application in Health, Assistance, and Entertainment, Las Vegas, NV, USA, 15–20 July 2018; pp. 250–262.
13. BenAbdelkader, C.; Cutler, R.; Davis, L. Person Identification using Automatic Height and Stride Estimation. In Proceedings of the 2002 International Conference on Pattern Recognition, Quebec City, QC, Canada, 11–15 August 2002.
14. Srinivasan, V.; Stankovic, J.; Whitehouse, K. Using Height Sensors for Biometric Identification in Multi-resident Homes. In Proceedings of the Pervasive Computing (Pervasive 2010), Helsinki, Finland, 17–21 May 2010.
15. Zacharaki, E.I.; Deltouzos, K.; Kalogiannis, S.; Kalamaras, I.; Bianconi, L.; Degano, C.; Orselli, R.; Montesa, J.; Moustakas, K.; Votis, K.; et al. FrailSafe: An ICT Platform for Unobtrusive Sensing of Multi-Domain Frailty for Personalized Interventions. *IEEE J. Biomed. Health Inform.* **2020**, *24*, 1557–1568. [[CrossRef](#)] [[PubMed](#)]
16. Jung, D.; Kim, J.; Kim, M.; Won, C.W.; Mun, K.R. Frailty Assessment Using Temporal Gait Characteristics and a Long Short-Term Memory Network. *IEEE J. Biomed. Health Inform.* **2021**, *25*, 3649–3658. [[CrossRef](#)] [[PubMed](#)]
17. Arshad, M.Z.; Jung, D.; Park, M.; Shin, H.; Kim, J.; Mun, K.R. Gait-based Frailty Assessment using Image Representation of IMU Signals and Deep CNN. In Proceedings of the 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Guadalajara, Mexico, 1–5 November 2021.
18. Rainoldi, A.; Donini, L.M.; Brustio, P.; Mulasso, A.; Poggiogalle, E.; Zia, G.; Feletti, L.C.; Signore, S.D. ADAMO indoor mobility, physical frailty, and autonomy in older adults: A mediation model. *Innov. Aging* **2019**, *3*, S681–S682. [[CrossRef](#)]
19. Ciubotaru, B.-I.; Sasu, G.-V.; Goga, N.; Vasileanu, A.; Popovici, A.-F. Architecture of a Non-Intrusive IoT System for Frailty Detection in Older People. *Electronics* **2023**, *12*, 2043. [[CrossRef](#)]
20. Mainetti, L.; Prono, L.; Secco, A.; Sergi, I. An IoT-aware AAL system for elderly people. In Proceedings of the 2016 International Multidisciplinary Conference on Computer and Energy Science (SpliTech), Split, Croatia, 13–15 July 2016.
21. Mainetti, L.; Prono, L.; Secco, A.; Sergi, I. An IoT-aware AAL System to Capture Behavioral Changes of Elderly People. *J. Commun. Softw. Syst.* **2017**, *13*, 68–76. [[CrossRef](#)]
22. Jayo, A.B.; Aimeida, A.; Sergi, I.; Montanaro, T.; Fasano, L.; Emaldi, M.; Patrono, L. Behavior Modeling for a Beacon-Based Indoor Location System. *Sensors* **2021**, *21*, 4839. [[CrossRef](#)] [[PubMed](#)]
23. Middleton, A.; Fritz, S.L.; Lusardi, M. Walking speed: The functional vital sign. *J. Aging Phys. Act.* **2015**, *23*, 314–322. [[CrossRef](#)] [[PubMed](#)]
24. Fried, L.P.; Tanen, C.M.; Walston, J.; Newman, A.B.; Hirsch, C.; Gottdiener, J.; Seeman, T.; Tracy, R.; Kop, W.J.; Bruke, G.; et al. Frailty in Older Adults: Evidence for a Phenotype. *J. Gerontol. Med. Sci.* **2001**, *56*, M146–M156. [[CrossRef](#)] [[PubMed](#)]
25. Steele, R.; Lo, A.; Secombe, C.; Wong, Y.K. Elderly person's perception and acceptance of using wireless sensor networks to assist healthcare. *Int. J. Med. Inform.* **2009**, *78*, 788–801. [[CrossRef](#)] [[PubMed](#)]
26. Espressif Systems. Available online: <https://www.espressif.com/en> (accessed on 22 May 2023).
27. ESPPerfectTime. Available online: <https://github.com/hunamizawa/ESPPerfectTime> (accessed on 16 May 2023).
28. Lunardini, F.; Luperto, M.; Romeo, M.; Renoux, J.; Basilio, N.; Krpič, A.; Borghese, N.A.; Ferrante, S. The MOVECARE Project: Home-based Monitoring of Frailty. In Proceedings of the 2019 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), Chicago, IL, USA, 19–22 May 2019.
29. Almaiah, M.A.; Almomani, O.; Alsaaidah, A.; Al-Otaibi, S.; Bani-Hani, N.; Hwaitat, A.K.A.; Al-Zahrani, A.; Lutfi, A.; Awad, A.B.; Aldhyani, T.H.H. Performance Investigation of Principal Component Analysis for Intrusion Detection System Using Different Support Vector Machine Kernels. *Electronics* **2022**, *11*, 3571. [[CrossRef](#)]

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