Cyber Physical System for pre-operative patient Prehabilitation

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Attestation of Authorship

"I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgments), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning."

Khalid Abdulrazak Mahmood Al Naime :
Date: 7/3/2022

Abstract

Abdominal cancer is the one of the most frequent and dangerous cancers in the world, particularly among the elderly, and is considered one of the leading causes of death in New Zealand and throughout the world. Major surgery is associated with a significant deterioration in quality of life, as well as a 20%-40% reduction in postoperative physical function. Physical fitness and level of activity are considered important factors for patients with cancer undergoing major abdominal surgery. These patients are often given exercise programmes prior to surgery (prehabilitation), aimed at improving fitness to reduce perioperative risk. Even though the number of prehabilitation programmes has increased over the last decade, there are many obstacles preventing large numbers of patients being involved in such programmes. One key problem is access to prehabilitation facilities and resources. The long-distance travel to vital cancer services can have a significant impact on a patient's quality of life and survival. Furthermore, limited numbers of healthcare centres and staff impact on the number of patients who can participate in supervised prehabilitation programmes. Unsupervised prehabilitation programmes have problems such as uncertainty of compliance with home-based exercises. Also lacking are measurements for the movements that are performed in relation to the intended frequency and intensity. Patient safety is also an issue with an unsupervised programme.

To minimise the above barriers, a model for a mixed mode prehabilitation programme has been designed. An environment for hosting the prehabilitation tracking model has also been developed. The end result proposes an end-to-end solution that provides patients and healthcare staff with a real-time remote monitoring and visualisation system. Furthermore, architectural features were recruited for this work to balance the computational load between the IoT device, gateway and cloud. This has facilitated better usage of the available environment through fewer messages, and the sharing of resources has reflected positively on overall system performance, such as:

a. The system showed high performance with activity recognition percentages ranging from 70%-94% when using the personalised database.
b. Different logical methods (M1, M2, M3, and M4) for activity recognition were implemented and embedded at the gateway level.
c. Using a mixed mode enabled detecting both casual and formal activities relevant to the prehabilitation programme. Also, the system offers real-time feedback on patients' progress during the prehabilitation period.

On the other hand, many challenging areas require additional research to provide better system performance, such as using artificial intelligence (AI) techniques in various embedded IoT devices

and differentiating between the different weights credited to different types of movement and activities.

This thesis is divided into seven different chapters, each accounting for a specific element of the overall work. The motivational background for the rising demand for healthcare monitoring is presented in the first chapter. The second chapter accounts for a critical review of the existing literature pertaining to the various key elements and boundaries associated with constructing a mixed mode prehabilitation model. The third chapter provides information related to the tools used for the implementation of hardware and software in the testing and verification of concepts. Chapter 4 proposes a conceptual mixed mode prehabilitation model based on existing rules and health programmes. Chapter 5 examines the various components of CPS in terms of data collection, data analysis, activity recognition, data visualisation, and short- and long-term data storage. Chapter 6 presents the clearly defined validation output data of the developed mixed mode prehabilitation model. The conclusions of this thesis, as well as the future path of the work, are presented in Chapter 7. Finally, this work has delivered four articles that have been published in international journals and conferences, and two proposed papers are under development to state the research outcome.

Acknowledgments

In the name of Allah, the most Gracious, the most Merciful.

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This thesis is dedicated to my parents' souls. I am eternally grateful to them for everything they have done throughout their life to support me and my siblings.

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List of Abbreviations

3D	3 dimensions
6MWT	6 minutes walking test
A	Amplitude
ADL	Human Activities of Daily Living
API	Application Programming Interfaces
AT	Anaerobic Threshold
BMI	Body mass index
CAR	Code of activity recognition
CPET	Cardiopulmonary Exercise Testing
CPS	Cyber-physical system
CSV	Comma-separated value
CT	Cross-trainer
CY	Cycling
ERAS	Enhanced Recovery After Surgery
D_e	Time per session
F	Frequency
FFT	fast Fourier transformation
FSL	Free space loss
GPIO	General-Purpose Input/Output
G_T	Total accumulated credits
GYM	Gymnasium
Hz	Hearts
I	Intensity
IMU	Inertial measurement units
IoT	Internet of things
K	The maximum number of allowable bed rest
LOS	line of site
LP	Leg press
LYI	Lying
M1	Method 1
M2	Method 2
M3	Method 3
M4	Method 4
NR	Non-Recognised
NSA	Nonspecific activity
PCA	Principal Component Analysis
R	Recognised
R_b	Bed rest
RO	Rowing
RPE	Rating of Perceived Exertion
RPi3B	Raspberry Pi 3B
RPiZW	Raspberry Pi Zero W

RPM	Revolution per minutes
RTC	Real time clock
RU	Running
RX	Receiving
SBC	Single-board computer
SIT	Sitting
SP	Step Up
STAD	Stair's ascending
STD	Standing
STN	Stair's descending
STU	Stair's ascending
T	Threshold
TIMSK	Timer Interrupt Mask
TM	Treadmill
TS	ThingSpeak
TX	Transmitting
VO2max	Maximum oxygen uptake
W	Walking
WAL	Walking Low
WSD	Wearable sensor device
WSN	wireless sensor networks
X	X-axis's
Y	Y-axis's
Z	Z-axis's

Chapter 1 Introduction

1.0 Introduction

The Internet of Things (IoT) and wireless sensors are rapidly spreading, with multiple applications in education, industry, and healthcare. Microprocessors, low-power radio technologies, wireless communication systems, and small-scale energy supplies have enabled low-power multi-functional sensor devices to detect and respond to changes in their environment. A sensor device consists of a microprocessor, a small battery, and a set of transducers, which are used to acquire information relating to the environment surrounding the sensor device. Telehealth is one of the key fields which is focusing on the development of IOT techniques and wearable sensor devices.

This chapter will commence with an overview of the role of the prehabilitation programme and the positive impact this intervention has on patients who are scheduled for abdominal surgery. Section 1.1 will briefly explain the role of the physical activity and its effect on the fitness and health of elderly people. Then section 1.2 will discuss the existing models of the prehabilitation programme and related challenges. In section 1.3, the role of the cyber physical system for supporting the prehabilitation programme will be discussed. The research aim, motivations, research scope and contributions are discussed in sections 1.4 and 1.5. Section 1.6 discusses the thesis organisation and section 1.7 demonstrates the research outcomes and publications.

1.1 The Role of Physical Activity

For the majority of cancer patients in an elderly population, participating in physical activity has been shown to lessen all-cause mortality, morbidity, and disability, and is beneficial for improvements in health outcomes in cardiovascular, metabolic and respiratory diseases and cancer [1]. The American College of Sports Medicine and the American Heart Association recommend that regular physical activity is essential for healthy aging and should include moderate-intensity aerobic activity for 30 minutes per day at least five times per week, along with strengthening, balance, and flexibility exercises [2]. Engaging in regular physical activity helps to provide a protective effect against many functional limitations [3]. An elevated level of physical activity is associated with a significantly reduced risk for incidence of colorectal cancer, and lower physical activity is known to be a risk factor for the development of abdominal cancer [4]**.** Physical activity has also been associated with improved short-term surgical outcomes [5], thus facilitating early recovery. Therefore, attempts to improve quality of life should be made by enhancing the level of physical activity patients engage in prior to surgery.

As the population ages, there is a reduction in physical function [6] often resulting in frailty. It is thus of importance to preserve and/or enhance cardiopulmonary function, muscle and bone strength and mobility [7] in cancer patients, due to the adverse effects of surgery, chemotherapy and radiotherapy. Not only does physical activity have a positive effect physically, but also psychologically [6]. Physical inactivity is known to be the fourth most important risk factor for overall death, according to the World Health Organization [8], and has an association with different types of cancer, colorectal and breast included [9].

1.2 Prehabilitation For the Abdominal Cancer Patient

Abdominal cancer is the one of the most frequent and dangerous cancers in the world, particularly among the elderly, and is considered one of the leading causes of death in New Zealand and throughout the world [10, 11]. Abdominal cancer is the most prevalent neoplasm and the third most lethal disease, according to GLOBOCAN 2018 data, with an expected 783,000 deaths in 2018 [12]. A worldwide population of over 230 million people undergo major abdominal surgery each year [13]. With a growing and aging population and easier access to healthcare, these numbers are likely to increase [14]. Major surgery is associated with a significant deterioration in quality of life, as well as a 20%-40% reduction in postoperative physical function [15]. Exercise training has been shown to positively affect the maintenance of functional capacity and facilitate recovery from surgery. A literature review on the role of optimising functional exercise capacity in the surgical population during the preoperative time frame has demonstrated that this approach can have a positive impact on reducing postoperative complications, decrease the length of stay in hospital, and improve quality of life [16]. Treatments before surgery such as chemotherapy produce a reduction in patient fitness level. Prehabilitation is an emerging concept and can be defined as the process of enabling patients to withstand the stressor of inactivity associated with an admission to surgery through augmenting functional capacity [16].

There have been various studies conducted with the concept of prehabilitation as a primary intervention [17]. The combination of surgical resection with adjunct chemotherapy and radiotherapy can have an impact on the return of basic functions [18]. It is often the case that patients who experience complications after their surgical procedure and need adjunct chemotherapy are at a higher chance of having their treatment postponed, as the body is not physically ready to undergo another stressful intervention [15]. Figure 1.1 shows a schematic illustrating a comparison of the fitness levels of patients who are involved and non-involved in a prehabilitation programme before surgery [19-21].

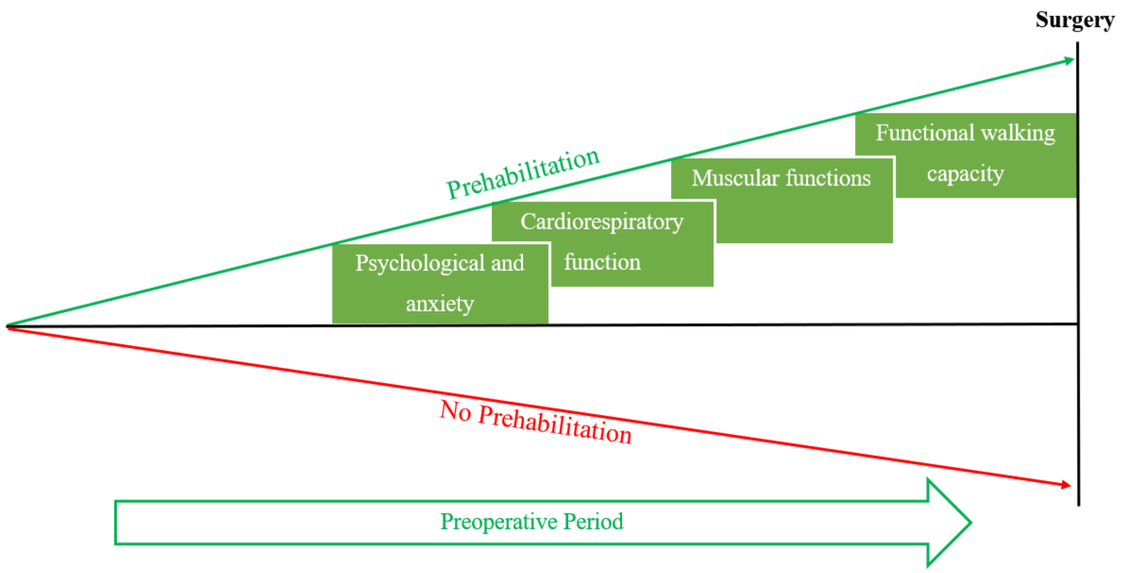


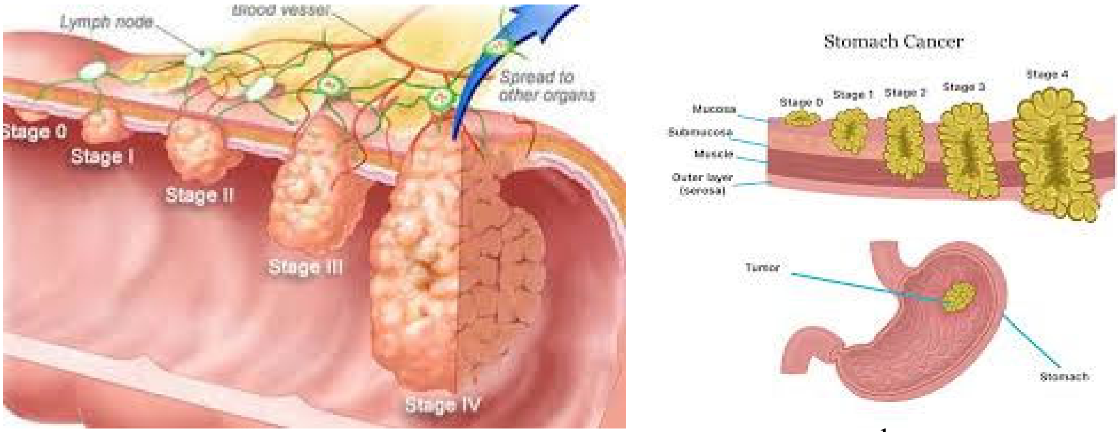
Figure 1.1 Schematic of the progress of patients during the preoperative period. The green line depicts the progression of patients who participate in the prehabilitation programme. Physical activity promotes functional capacity in the preoperative phase. The red line indicates the patients who did not participate in the prehabilitation programme.

1.2.1 Types of Abdominal Cancers

The term "abdominal cancer" refers to cancers that affect digestive system and abdominal organs such as the stomach, liver, large intestine, small intestine, pancreas, gallbladder, oesophagus, and rectum[22]. It happens when damaged or old cells rapidly divide and multiply, resulting in a malignant mass tumour [22]. As an example, Figures 1.2 a and b depict the various stages of colon and stomach cancers.

The main abdominal cancer types are : Colorectal cancer, Pancreatic cancer, , Stomach cancer [23]. Depending on the type of abdominal cancer, symptoms may vary. Many people experience no symptoms in the early stages of colorectal cancer, liver cancer, stomach cancer, and pancreatic cancer. Most of the above types have some general common symptoms such as [24]:

- Abdominal pain
- Appetite loss
- Blood in the stool
- Noticeable increase in fatigue and/or weakness
- Unexplained weight loss
- Nausea
- Vomiting



a b

Figure 1. 2 a Shows different stages of Colon cancer, **b.** Shows different stages Stomach cancer

However, treatment options are determined by the stage of cancer. Each has its own set of drawbacks. A combination of treatments may be recommended by doctors. One of the most common treatments, particularly in early-stage cancer, is surgery[25]. To be ready for the major surgery, the patient must undergo extensive preparations in terms of psychological fitness, physical fitness, nutrition, and general health conditions. Prehabilitation is one of the common fitness programmes recommended for abdominal patients undergoing major surgery [5, 7, 17, 26].

1.2.2 Existing Prehabilitation Programs

The two main prehabilitation models that are currently applied to patients undergoing major surgery are supervised and unsupervised programmes [5, 7, 17, 26]. Patients who are involved in the supervised programme usually perform the prescribed physical exercises under the direct supervision of a healthcare professional. A supervised in-person programme provided by a healthcare professional is considered the gold standard in terms of safety and effectiveness [27, 28]. Most supervised prehabilitation programmes documented in the literature occur in a hospital setting and tend to be supervised by an experienced health professional (e.g., physiotherapist, exercise physiologist, or trained nurse.). This type of prehabilitation is usually limited to those individuals who live in close proximity to a hospital [29]. Prehabilitation exercise sessions are typically performed in a gymnasium, and the type of equipment used in these settings ranges from simple (commercial equipment) [30] to sophisticated cycle ergometers with pre-set workload parameters [29, 31]. The number of required visits varies between studies, but most supervised programmes require participants to attend between two to three session per week [10, 31]. Exercise intensity/workload settings for the programmes are often based on cardiopulmonary exercise testing (CPET) findings. All these factors enable more controlled exercise prescription. However, supervised prehabilitation demands a high level of resources and is often limited to those individuals who live close to the prehabilitation facilities [29]. Figure 1.3 shows the general structure of supervised prehabilitation programmes.

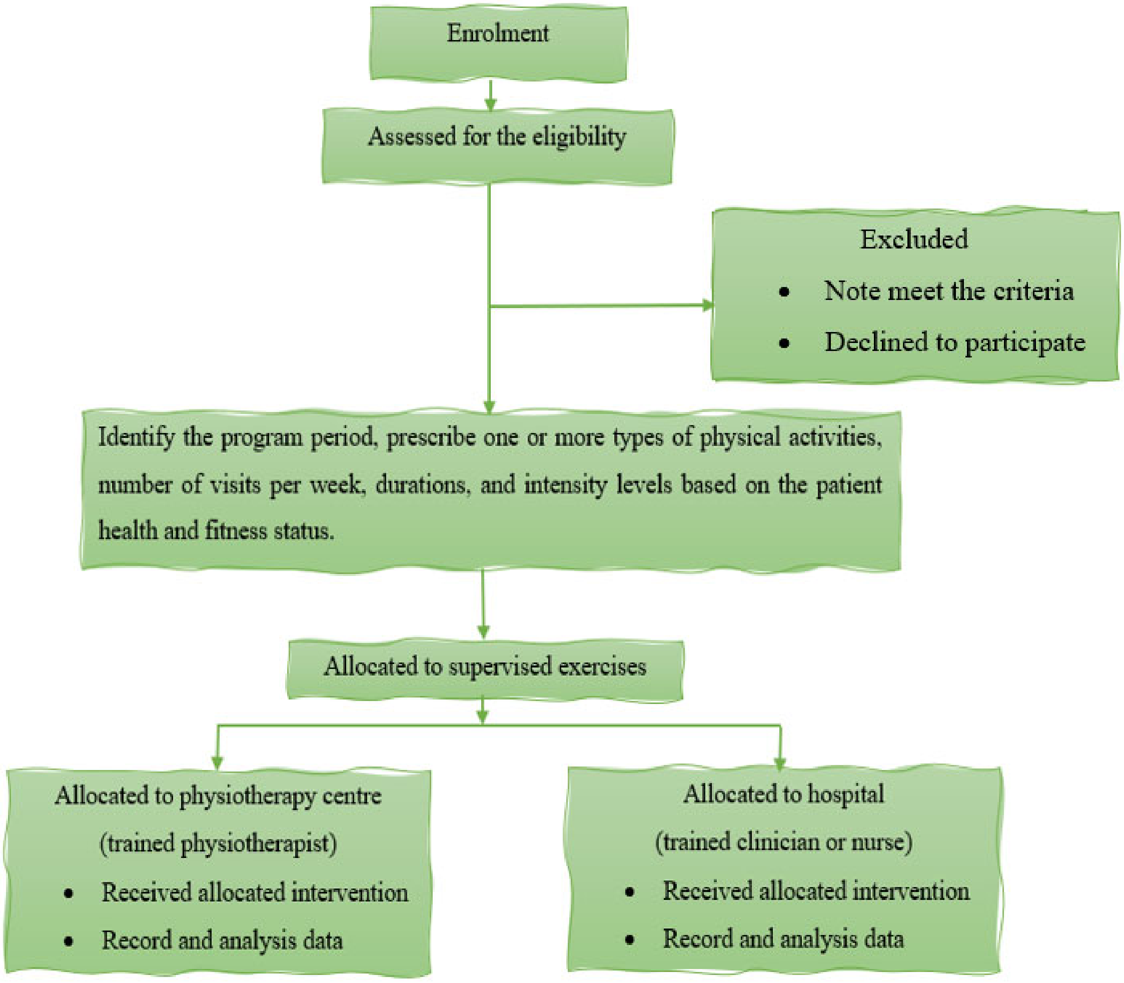


Figure 1.3 General structure of supervised prehabilitation program.

The home-based prehabilitation programme (unsupervised) offers flexibility for patients to perform the prescribed activity in their home or community centre (gymnasium) [31]. Another advantage of the home-based programme is that it overcomes geographical barriers; patients living outside the region may access services when they might not have had the opportunity due to the distance and time required to travel to the referral centres [31, 32]. Despite prescribed physical exercises being based on home-based prehabilitation programmes (unsupervised), they are similar to those in a supervised prehabilitation programme [5, 7, 10, 26, 31]. However, the lack of group sessions means that patients do not have access to peer support, which is felt to be important in addition to exercise. Furthermore, some patients believe that home-based approaches rely more on self-motivation than face-to-face appointments (supervised guidance) [32]. Phone calls and video interventions are common telehealth services used to guide patients during home-based prehabilitation programmes [27, 28, [33]. Based on pilot research [34, 35], the feasibility of adopting a home-based prehabilitation programme has been demonstrated. According to the findings of these trials, the majority of patients in the prehabilitation group were below their baseline values four weeks following surgery, indicating that the home-based programme was insufficient to encourage physical activity and daily life modifications. Lack of direction and supervision by a kinesiologist, resulting in patients not following the programme as advised, could be one reason for not returning to baseline measures. Figure 1.4 below shows the general unsupervised procedure for prehabilitation programmes.

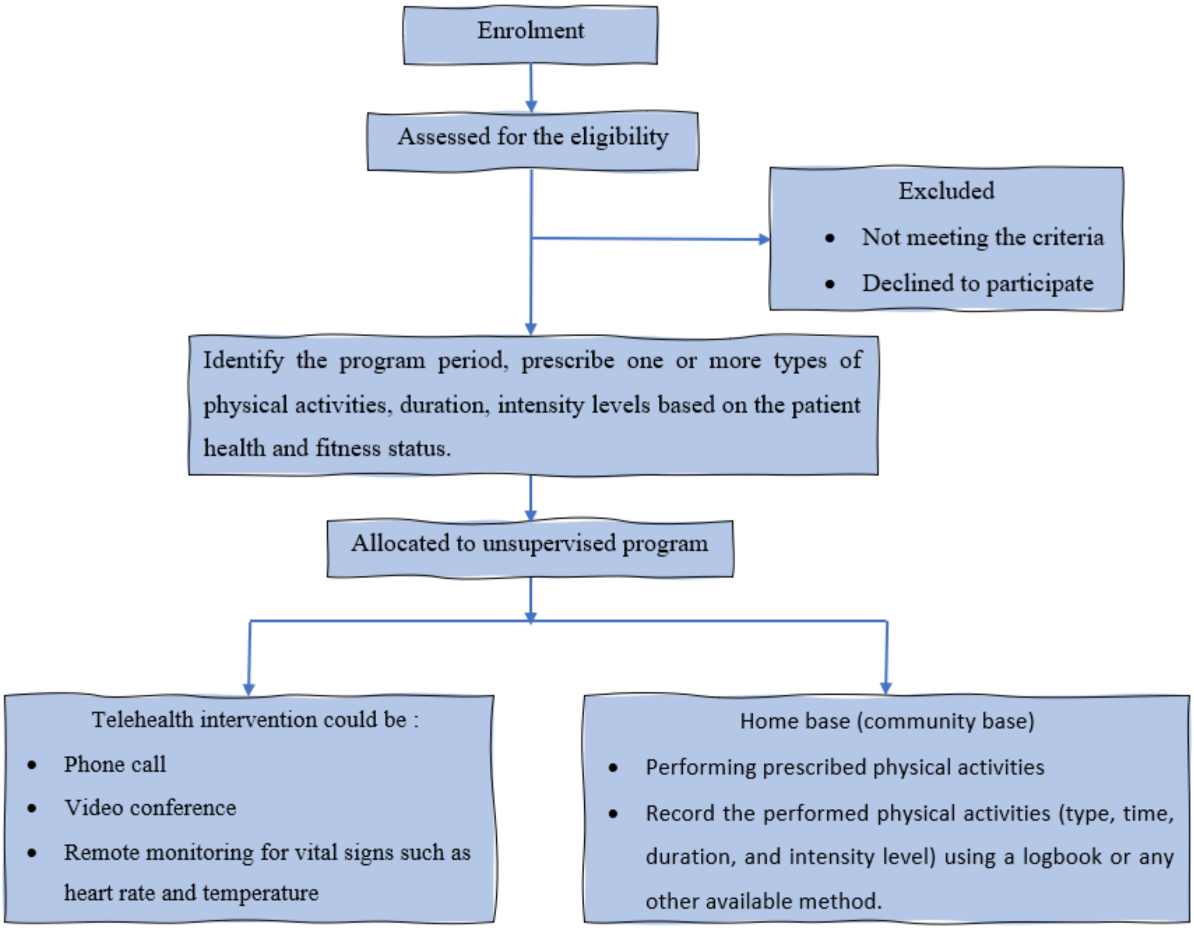


Figure 1.4 General structure of unsupervised prehabilitation program.

1.2.2 Barriers for The Prehabilitation Programs

Even though the number of supervised and home-based programmes has increased over the last decade, there are many obstacles preventing large numbers of patients being involved in such programmes. One key problem is access to prehabilitation facilities and resources. For example, people diagnosed with cancer who live outside of large urban regions have a much lower chance of surviving than those who live in cities [7, 8]. Patients in rural and regional areas are less likely to have their treatment monitored by an oncologist [9] or to have access to multidisciplinary specialist oncology services [9, 10]. The long-distance travel to vital cancer services can have a significant impact on a patient's quality of life and survival [11]. There is also consistent evidence that cancer patients face barriers to attending in-person supervised programmes. These include transportation, parking and time, as well as a desire to avoid additional hospital appointments [36]. Furthermore, limited numbers of healthcare centres and staff will impact on the number of patients who can participate in supervised prehabilitation programmes. Furthermore, transportation, healthcare centre visits, and demand on facilities are an additional burden for both the patient and the healthcare system [36].

Unsupervised prehabilitation programmes address a number of these issues but also have some problems. For example, there may be uncertainty that home-based exercises are performed at the intended frequency and intensity, and the lack of monitoring means that patient safety is an issue with the unsupervised programme. It has been shown that some cancer patients prefer flexible home-based programmes [23], but a study investigating experiences of such programmes found that some patients felt that greater involvement from healthcare professionals would increase engagement, especially if the patients were sedentary [24]. Given the inherent challenges of each approach, we contend that debating the best delivery mode (supervised versus unsupervised home-based) is a futile and counterproductive exercise. Rather, consideration should be given to how the limitations of any delivery mode can be addressed to provide programmes that are best suited to the local context. A number of the prehabilitation trials described below addressed this by combining supervised sessions with home-based elements [33, 37]. Community-based programmes that provide more readily available assistance have also yielded promising preliminary results [23]. Telehealth has the potential to address this health disparity and improve health outcomes [23] by providing an alternative for those who are unable to travel due to caring or work commitments [24, 25], conflicting clinical appointments, or treatment-related symptoms. The nature of telehealth interventions might range from instructive or helpful websites to computerised questionnaires and live online chats [23]. When presented to patients preparing for cancer surgery, patient education sessions involving audio-visual or multi-media treatments have been demonstrated to improve satisfaction and knowledge [23]. Evidence on telehealth in the perioperative context for cancer patients, on the other hand, is currently restricted to small cohort studies [24, 25].

1.3 Cyber Physical System for The Cancer Patient Prehabilitation

A cyber physical system (CPS) combines physical processes with computation and communication. It has the power to make social interactions more intelligent. Strong sensing capabilities are one of the key driving forces for CPS applications [38]. The recent advances in wireless sensor networks (WSN), medical sensors, and cloud computing are making CPS a powerful candidate for healthcare applications, including in-hospital and home-based patient care

[39]. Accordingly, a CPS can be considered as a new generation of systems with integrated control, communication, and computational capabilities [40, 41]. The integration of CPS applications in healthcare systems could be used to analyse data to find adaptive treatments for general population health. Furthermore, CPS has the potential to anticipate and predict changes in patient health status by automatically detecting changes in bio signals in real time [42]. Another important role of CPS is the personalisation of therapeutic interventions tailored to the patient's condition and the provision of feedback to health professionals to improve precision in making informed decisions regarding patient care [42]. Finally, CPS could have an impact on reducing the number of ineffective investigations that do not shed light on the patient's health difficulties, and instead conduct precise and adequate investigations resulting from an analysis of the patient's data [40]. Based on the above information, many of the barriers and obstacles that patients face during the prehabilitation programme could be overcome by a CPS. Real-time remote monitoring, activity recognition, effort calculations, transparency in data flow, data repository, visualisation, and remote healthcare interventions are key components of a CPS that offers support to the prehabilitation process. Accordingly, CPS is especially significant for individuals who live in rural areas and must plan ahead for appointment times with healthcare providers. Figure 1.5 demonstrates the general blocks of CPS, which involve the interplay between computer science, information, communication technology, and manufacturing.

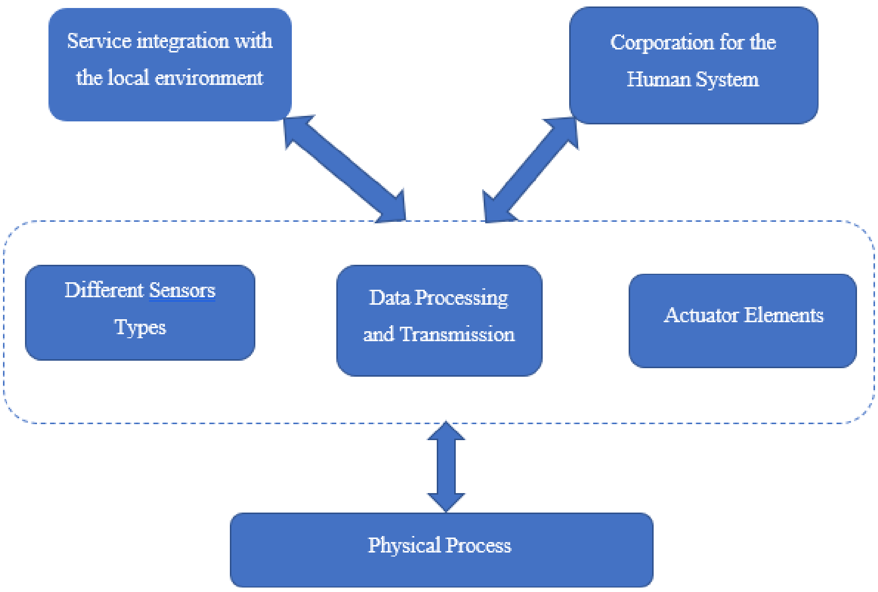


Figure 1.5 General structure of the cyber physical system.

1.4 Research Aim and Motivation

Most of the work in previous studies has focused on a single prehabilitation model (supervised or home-based) and included key parameters such as duration, type of physical activity, frequency, and intensity level to enhance the general fitness of the patient before major abdominal surgery [30, 43-45] . Very few studies have created a framework for the prehabilitation model based on both supervised and home-based training. In these studies, activity data was collected from the patient via telephone communication, camera surveillance, heart rate measures, temperature sensors, and basic movement detection by using accelerometers or recordings in a logbook [33]. The fundamental issue spurring on the debate is that no one delivery mode (home-based or supervised) offers a programme that is effective, safe, person-centred, and widely accessible. Accordingly, the aim of this research is to create a real-time monitoring system that can enable effective tracking and delivery of a mixed mode model of prehabilitation for abdominal cancer patients through the analysis of essential activity sensing, categorisation, and event detection.

1.5 Research Scope and Contribution

In this thesis, the key factors and boundaries of a mixed mode prehabilitation model will be discussed. A major part of this thesis will be the development and testing of a mathematical model that takes into consideration current standard prehabilitation practices, to determine the duration, type and intensity of physical activity performed by patients undergoing prehabilitation exercise interventions. A cyber physical system using IoT techniques is integrated into the activity performance model, which is designed and implemented to support the prehabilitation requirements. This involves movement recognition, calculations of physical effort, remote monitoring, data storage, and determining the maximum number of users for the system. For system validation, real-life scenarios are proposed and tested on individuals who have cancer or have similar demographics to abdominal cancer sufferers.

This thesis has many unique contributions. It develops a mixed mode prehabilitation model based on existing models by extracting the advantages of previous (supervised and home-based) prehabilitation models. It reflects the development of a mathematical model that is able to track the efforts made by people engaging in a prehabilitation programme and help the user and healthcare provider to visualise the patient's effort via numerical feedback. This thesis work contributes to a deeper understanding of existing prehabilitation models and their effects on the fitness and functional capacity of cancer patients when they participate in those models. The thesis will also discuss the prehabilitation programme challenges and propose some remedies. The variety of physical activities used for the prehabilitation of cancer patients, as well as their duration, frequency, and intensity levels, have all been defined and examined in this thesis. In addition, the thesis establishes and implements the IoT and CPS frameworks which support prehabilitation models in terms of activity recognition, remote monitoring, data storage, and data analysis.

1.6 Thesis Organization

The thesis consists of seven chapters that are summarised as follows.

Chapter 1 gives an overview of abdominal cancer and its impact on the healthcare system. It also discusses existing prehabilitation programmes for abdominal cancer and the important role of physical activities during these programmes, as well as the motivation and direction of the research work undertaken.

Chapter 2 describes the key components of the two prehabilitation models (supervised and unsupervised) that have been used to improve fitness in abdominal cancer sufferers prior to surgery. Prehabilitation outcome measurements methods and limitations are discussed. The available technology (WSD, gateway, cloud IoT-based) that is able to support the existing prehabilitation models is also reviewed and discussed.

Chapter 3 deals with the modelling and implementation tools for testing the different IoT parts, to support the mixed mode prehabilitation model. In this chapter, information is provided on the virtualisation and hardware tools employed towards concept simulation (implementation) and testing purposes.

Chapter 4 focuses on the development of the "mixed mode prehabilitation program" and cyber physical system that will support the prehabilitation model. Different aspects of the conceptual development of the mixed mode prehabilitation model and cyber physical system are discussed. This is done by firstly extracting the key elements and boundaries of the existing supervised and unsupervised models and outlining the advantages and disadvantages of each model, and then applying mathematical formulas to calculate the outcome in a numerical form. Technical specifications of each proposed element involved in the system are described in terms of the cyber physical system concept. Some of these elements include wearable sensor device boundaries and limitations in terms of edge computing, size, and power consumption, the gateway, and the role of IoT edge computing, data analysis, data transmission, and data repository. This chapter also explains the capability of visualisation via the cloud and long-term data repository and data analysis.

Chapter 5 focuses on the design and implementation of the mixed mode prehabilitation model and the cyber physical system. This chapter also presents key results from testing each component of the cyber physical system and describes the critical issues and limitations of each part of the cyber physical system in relation to the mixed mode prehabilitation model. Results from the different methods of physical activity recognition using the system for both healthy and cancer participants are also presented.

Chapter 6 demonstrates the results of different tests in different scenarios to evaluate the overall system specifications, features, and limitations. In this chapter, a mixed mode prehabilitation model is tested on participants engaged in six weeks of prehabilitation activities, and key outcomes such as activity recognitions, accumulated gain, and time are presented.

Chapter 7 concludes this thesis with suggestions for future research work.

1.7 Research Outcomes - Publications Based on The Thesis Work

A total of four papers have been published over the course of this PhD research. Two of these have been published in the MDPI journal [46, 47] and the third was presented at the 6th International Conference, ICT4AWE 2020 [48]. The fourth paper was published as a Part of the Communications, Computer, and Information Science Springer book series (CCIS, volume 1387) [49]. The conceptual basis behind the proposition advanced within this research work (that of driving towards design and implementation of both a mixed mode prehabilitation model and a cyber physical system) has been reflected within these publications.

Publications related to the thesis

1- K. Al-Naime, A. Al-Anbuky, and G. Mawston, "Human movement monitoring and analysis for prehabilitation process management," *Journal of Sensor and Actuator Networks,* vol. 9, no. 1, p. 9, 2020.

2- K. Al-Naime, A. Al-Anbuky, and G. Mawston, "Remote monitoring model for the preoperative prehabilitation program of patients requiring abdominal surgery*," Future Internet, vol. 13, no. 5, p. 104, 2021.*

3- A. Gupta, A. Al-Anbuky, and K. Al-Naime, "IoT Based Testbed for Human Movement Activity Monitoring and Presentation," *6th International Conference on Information and Communication Technologies for Ageing Well and e-health, 3-5 May, 2020, Prague, Czech Republic, pp. 61-68, doi: 10.5220/0009347800610068.*

4- A. Gupta, K. Al-Naime, and A. Al-Anbuky, "IoT environment for monitoring human movements: Hip fracture rehabilitation case," *International Conference on Information and Communication Technologies for Ageing Well and e-Health*, 2020: Springer book series, pp. 44-63.

Chapter 2 Literature Review

2.0 Introduction

Abdominal cancer is one of the leading causes of death in New Zealand and throughout the world [10, 11]. A burden of disease study conducted in NZ found that cancers contributed 20% to the total burden of disease, second only to cardiovascular diseases, at 24% [11, 50]. A reduction in quality of life is common with many types of cancer and is associated with symptoms such as fatigue, pain, or impaired function, which affect work, family life and recovery [12]. Symptoms usually last for several years and lead to chronic illness and multimorbidity [51]. Most survivors do not reach their level of function prior to cancer diagnosis, and report persistent fatigue, cognitive impairment, depression, anxiety, sleep problems, and pain for up to ten years after diagnosis [51].

One of the most common interventions for abdominal cancers is surgical resection of the adenocarcinoma. Surgical resection of tumors has the potential to significantly improve five-year mortality rate, particularly when used in conjunction with neoadjuvant therapy [52]. However, surgery and postoperative care often result in a prolonged duration of physical idleness and deconditioning, as well as loss of muscle strength and an increased risk of health complications [53]. For cancer patients experiencing critical abdominal surgery, physical fitness is a key concern. Patients exhibiting inadequate aerobic fitness have been shown to have a higher risk of postoperative complications, which have been associated with prolonged length of stay in the hospital and greater mortality rates [54]. Additionally, a high number of patients receive neoadjuvant therapy such as radiotherapy and chemotherapy before undergoing surgery, which impairs aerobic potential.

The time gap between the end of neoadjuvant therapy and the surgical procedure is usually four to six weeks [4]. Numerous patients fail to do the same activities of daily life as they did prior to neoadjuvant therapy, due to the multiple complexities involved [15]. As a result, prehabilitation offers the chance to address the physiological deficits prior to surgery, enhance quality of life and reduce patient-related obstacles such as the stress of surgery. Quick and improved procedures focusing on the pre and postoperative phases have been linked to a 30% decrease in postoperative complications, one or more days reduction in hospitalisation, and decreased likelihood of readmission [45]. Minor surgery, multimodal analgesia, early nutrition, and preoperative mobility are among the Enhanced Recovery after Surgery (ERAS) guidelines that have boosted patient outcomes after surgery. Irrespective of these advancements, surgery causes a 20%-40% decrease in postoperative functional ability, as evaluated by energy consumption, tolerance duration, volume of work, and heart rate under a maximal exercise routine [55].

A four-to-six-week term has been employed in various hospitals to design exercise programmes aimed at increasing physical fitness in this cohort of patients before undergoing surgery. Prehabilitation is a phrase used to describe the process of optimising functional ability in the preoperative phase in order to augment tolerance for the approaching strain of surgery [44].
Exercise programmes for "prehabilitation" can be supervised as well as unsupervised (home-based activities). Nonetheless, the type and intensity of workouts employed in some of these programmes differ to a great extent [27, 28]. Although the exercises and their intensities are usually developed and supervised by specialists in a clinical setting (hospital or outpatient clinics/gymnasiums), there is little empirical evidence to show that patients engage in the prescribed exercises outside the clinical environment [31, 33]. These findings of reduced activity engagement outside the hospital setting are apparent, despite the increased availability of indoor exercise facilities (e.g., fitness clubs, sports centres, dance clubs, and Pilates studios) that offer physical activity programmes [56] and outdoor recreational facilities (e.g., public parks and outdoor playing fields) designed to encourage physical activity.

It has been proposed that the reduced engagement in unsupervised home-based prehabilitation may be due to a lack of objective identification and monitoring of the kind and intensity of exercises performed by patients throughout supervised prehabilitation [33]. Furthermore, without adequate monitoring, it is difficult for clinicians to adjust programmes and provide feedback to patients undertaking home or community-based prehabilitation. The development of a tool that provides clinicians with crucial information about the patients' exercise regimes and enables therapists to share their reviews with the patients has the potential to address key issues associated with non-supervised home-based prehabilitation [57, 58].

2.1 Prehabilitation Mode and Physical Exercise Involved.

Prehabilitation for cancer surgery has attracted much interest from researchers in recent years. Several organisations have used various techniques for treating patients during the prehabilitation phase, keeping aerobic fitness activities as a major component of their therapies. These programmes may be classified into two types of prehabilitation styles, namely, supervised and unsupervised programmes.

2.1.1 Supervised Prehabilitation Model.

Several hospitals and researchers have worked together over the last two decades to develop supervised prehabilitation programmes for patients who have undergone critical abdominal surgery. Jones et al. and Peddle et al. [11, 12] examined the impact of exercise prehabilitation on 13 cancer patients with an average age of 65 years suffering from stage I to stage III abdominal cancer. The researchers developed a supervised aerobic exercise regimen that included 20 to 30 minutes of exercise five times per week at 60%-65% of maximal oxygen consumption (VO2 max) over the course of approximately four weeks. Patients were subjected to interval training on an exercycle after the fourth week at a ratio of six minutes on and one minute off, to four minutes on to one minute off (6:1 to 4:1). Five minutes of warm-up and cool-down activities were included in each session. Dronkers et al. [13] investigated 42 individuals with an average age of 68 years. These patients exercised at physiotherapy treatment centres for an hour twice every week. The exercise regime for weeks 2 to 4 consisted of aerobics training at an intensity of 55%-75% of maximum heart rate or a rating of perceived exertion (RPE) of 10-13/20, along with 20-30 minutes' training of resistance exercises, comprising one set of 8-15 repetitions. Subjects also received training for inspiratory muscle conditioning and were advised to exercise at home. They were given a pedometer to track their activity levels. Heldens et al. [14] investigated the impact of a hospital-supervised programme on 13 subjects. The regimen included 45 to 60 minutes on the treadmill and/or rowing activity twice a week at a magnitude of 50%-60% maximal heart rate, as well as resistance exercises (leg press, chest press and lateral pull-down). Karin et al. [15] included 115 participants in a six-week exercise programme supervised by a physiotherapist. The exercise was mostly performed on a rowing machine, cross trainer and stationary cycle for 20-30 minutes five times a week at an intensity of 60%-85% of maximum heart rate. Carli et al. [16] invited 110 patients suffering from abdominal cancer to attend a training programme conducted by an expert kinesiologist at the prehabilitation unit of a hospital once a week for approximately a month. In these sessions, the patients were required to do moderate aerobic activity on a recumbent stepper (including a five-minute warm-up) for a total of 30 minutes, along with resistance exercises with an elastic band for 25 minutes and stretching for five minutes.

The primary theme behind these prehabilitation programmes was to encourage patients to attend the hospital or physiotherapy facility and complete a series of physical activities under the supervision of a health professional. The number of appointments, the timing of each visit, and the length of the programme varied for all patients, depending on their health status (see Table 1 for details). One of the key benefits of this paradigm is that the patient does the recommended physical exercises under direct observation. While the overhead costs for the patient as well as the healthcare system are regarded as the main disadvantages of this model, the demand for appropriately trained healthcare staff at the prehabilitation centres, as well as the geographical distance between the hospital and the patient, are regarded as additional constraints.

2.1.2 Unsupervised Prehabilitation Model

The unsupervised model is centred on recommending patients to complete specified physical exercises at home. For example, Nielsen et al. [59] conducted their research on 80 patients between the ages of 31-80. They performed home-based activities led by a physiotherapist as part of a prehabilitation course two weeks before surgery. For a span of six to eight weeks, the programme required each participant to perform 30 minutes of regular activities, with an emphasis on strengthening back and abdominal muscles, as well as upper limb exercises, without recording the precise intensity. In another study, Gillis et al. [18] chose 38 cancer patients of various ages and enrolled them in unsupervised prehabilitation therapy, which included fitness instruction consisting of unsupervised home-based exercises for up to 50 minutes three times a week. Aerobic and resistance activities were incorporated into the workout, wherein the intensity of aerobic exercises was calculated via the Karvonen technique, and (RPE) deduced from the six-minute walk test (6MWT). Aerobic activities like cycling, jogging, walking or swimming were self-selected by individual patients. Every session started with a five-minute warm-up, followed by 20 minutes of aerobic activity (beginning at 40% of maximum heart rate), 20 minutes of resistance training, and a cool-down for five minutes. The training intensity increased after the subject was able to perform the aerobic workouts continuously at an RPE of 12 and when they achieved 15 repetitions of a specified resistance exercise. Patients were supplied with heart rate monitors to indicate intensity during aerobic exercises, along with resistance bands that were utilised for home-based resistance training.

In another study, Sekine et al. [19] employed several approaches of prehabilitation on a group of 82 patients with an average age of 70 years. The training consisted of a 30-minute daily breathing exercise paired with a goal of attaining 5000 steps per day for two weeks, with no intensity recorded. In another study, participants were given a tailored home-based programme of aerobic activities (walking every day for 30 minutes or a moderate-intensity aerobic exercise) and resistance training (an elastic band regime three times a week) in line with the recommendations of the American College of Sports Medicine [60].

Table 1 depicts an overview of the period, length, frequency, and physical activities involved in unsupervised prehabilitation programmes. This approach provides flexibility and minimal cost to patients, while reducing the economic burden on the healthcare system. However, the primary drawbacks of this paradigm include ambiguity about the patient completing the recommended physical exercises, and the poor consistency of recording activity information and communicating progress to the patient. In addition, unsupervised home-based programmes are not as effective for improving pre-surgical levels of aerobic fitness when compared to supervised hospital-based programmes [34, 35].

Table 1. Examples of exercise parameters used in supervised and unsupervised prehabilitation programmes for cancer patients undergoing abdominal surgery.

Study	Prehabilitation period	Frequency of Exercise	Activities	Intensity
Supervised Prehabilitation				
Jones et al & Peddle et al,[11, 12]	four-eight weeks	20-30 minutes, five times per week	cycling & interval training	light, moderate & vigorous
Dronkers et al, [13]	two-four weeks	60 minutes, two times per week	aerobic training, resistance exercise with inspiratory training	moderate & vigorous
Heldens et al., [14]	no record	45-60 minutes, two times per week	treadmill, rowing, and resistance exercise (leg press, chest press and lateral pull-down)	moderate
Karin et al, [15]	six weeks	20-30 minutes, five times per week	cross trainer, rowing, cycling	moderate & vigorous
Carli et al [16]	four weeks	30 minutes daily	Walking and aerobic training	moderate
Unsupervised Prehabilitation				
Nielsen et al, [55]	six-eight weeks	30 minutes daily	strengthening of back & abdomen muscle concentration on an upper limb only	no record
Chelsia Gillis et al, [18]	four weeks	50 minutes, three times per week	walking, running, cycling and resistance exercises	light, moderate & vigorous
Sekine et al, [19]	two weeks	30 minutes daily	pulmonary exercises- extensive breathing exercise & Walking	no record

2.1.3 The Need for Prehabilitation and The Associated Time Frame

Preoperative exercise therapy, including both aerobic and resistance training, has proven to be the hallmark of prehabilitation [61]. The length of prehabilitation varies from patient to patient and is determined by a variety of criteria such as the patient's fitness, age, and stage of cancer, but typically ranges from two to eight weeks. Table 2 displays the features of the exercise programme and the schedule for cancer patients in various countries undertaking prehabilitation prior to their abdominal surgery.

Table 2. Examples of primary studies in prehabilitation exercises for abdominal surgery [62].

Country	Population	Intervention
UK [63]	Colorectal	30 min of daily supervised exercise over six weeks
Japan [64]	Gastric	aerobic three to seven times per week, resistance one–two times per week, over four weeks
France [65]	Transplant hepatobiliary	20 min aerobic, 20 min strength per session, two times per week for 12 weeks
Canada [66]	Colorectal	home-based aerobic exercise prescription over four weeks
The Netherlands [67]	Abdominal	variable duration of intervention, two times per week, two hours aerobic and strength exercise per session
Brazil [68]	Bariatric	six times per week, 15 min inspiratory muscle training "IMT" session for two to four weeks

2.1.4 Measurement of Physical Exercise Intensity Levels.

According to the research, the type, frequency, and duration of exercise employed in cancer prehabilitation programmes is highly diverse, as shown in Table 1 above. The primary role of accelerometry when monitoring exercise in cancer populations has traditionally been to measure step count [69, 70]. Yet an important parameter to measure during such short-duration prehabilitation is exercise intensity, as moderate to high intensity exercise is required for improvements in aerobic capacity and better post-operative outcomes [71-73]. Research has typically categorised the intensity of physical activities using speed, wattage, and cadence measurements, and physiological measures such as heart rate and RPE [74, 75]. Recording of these measures in the home-based setting often requires complex equipment such as heart rate monitors or is reliant on patients documenting type and intensity of activities in a logbook. However, more advanced three-dimensional accelerometry measurement has developed the potential to detect intensity levels during activities like walking, running, and cycling. The intensity of exercises like these can be categorised as “light,” “moderate,” or “vigorous” [76]. For instance, walking speeds of 3.3 km/h, 4.2 km/h and 6 km/h have been identified as light, moderate and vigorous intensities, respectively [77]. At the same time, speed rates of 8.3 km/h and 4.2 km/h have been shown to reflect moderate jogging and moderately ascending and descending staircases, respectively [77]. Other research has identified 4.8 km/h, 6.4 km/h, and 9.6 km/h for low, moderate, and strenuous walking on a treadmill, respectively [78]. It has been argued that these changes in walking and running speeds produce different accelerometer measures/profiles, which, in turn, can be used to detect the intensity of the exercise that is being undertaken [79]. Other activities and their intensity tend to produce different acceleration profiles to walking and running. For example, cycling produces different acceleration profiles to running, [80] and intensity can be increased by elevating cadence from 60 to 80 to 100 RPM, which can also produce unique accelerometry profiles [81]. Rowing intensity is also calculated by monitoring the average power output of the rowing ergometer, reflecting the intensity level. For example, a power output of 40 W from a rowing ergometer for three minutes' duration is deemed baseline or low intensity, but an output of 80 W is rated moderate intensity [82]. However, the intensity range for other exercises such as cross trainer, step ups, squats, and leg press need further exploration.

2.2 Prehabilitation Performance Measurement

Prehabilitation programmes are primarily targeted at improving functional capacity and aerobic fitness in people with abdominal cancer. The primary tool for measuring improvements in fitness in this population is cardiopulmonary exercise testing (CPET). CPET requires the patient to perform an incremental cycle or treadmill test to exhaustion. During CPET, breath by breath gas analysis is performed to determine oxygen consumption and carbon dioxide production, and other respiratory and heart rate measures are recorded continuously throughout the test. The two key parameters that are used to determine perioperative risk are anaerobic threshold (AT) and maximum oxygen uptake (VO2 max). Improvements in these parameters following a prehabilitation programme have been shown to reduce post-surgical complications, length of hospitalisation and mortality risk [66, 83, 84]. The main disadvantage of this method is the high cost involved, and the patient typically has to perform this assessment in a hospital under the supervision of a trained doctor.

In situations where CPET is not available, the most common clinical test used to assess improvements in functional capacity is the six-minute walk test. The six-minute walk test (6MWT) measures the maximum distance the patient can walk in six minutes [37-39, 11]. This test assesses a person's capacity to maintain a fair level of walking during a daily routine. The six-minute walk test has high reliability, provided the participant has a practice trial, is simple to administer, acceptable, and endorsed for the surgical population. The 6MWT can easily be performed by the patient; however, the drawback of this method is that it is not able to produce a precise measure of aerobic capacity (VO2 max) during the prehabilitation period.

Modern gadgets, like Apple watches, Grit X watches, and Garmin watches, can all assess VO2 max. The issue with these meters is that they are costly and offer an inaccurate VO2 max estimation, especially for people who are suffering from different health issues to abdominal cancer [85]. Many factors diminish wristwatch VO2 max measurement accuracy, including human skin (darker skin reduces reading accuracy) and high intensity exercise [86, 87].

2.3 Prehabilitation: Key Elements for a Cyber-Physical System Approach

Developing a cyber physical system, which can detect and oversee physical activities during the prehabilitation period, must involve the designating of basic parameters of physical activities (type, intensity, frequency, and duration) over time. The model should also provide the opportunity for medical doctors or physiotherapists to oversee patients executing their prescribed physical exercises in real time.

The Internet of Things (IoT) unquestionably provides a system to fulfil the defined platform.

The IoT platform is a collection of components that enables developers to distribute applications, collect data remotely, and run secure connectivity and sensor management.

However, to render the IoT more suitable for the prehabilitation programme, several basic sub-elements and tasks must be included. These are: characteristics of the subject group that is going to be monitored, wearable wireless devices for sensing and measurement, the embedded software that acquires sensor data and analyses the data for identifying the type of movement performed by the subject, and data and information communication facilities for various levels of interaction. The subject group characteristics sub-element involves human subject data such as age, level of health, and presence of co-morbidities. It also covers the environment in which the activities are monitored (e.g., physiotherapy centre or in a free-living environment). On the whole, prehabilitation applies to male and female cancer patients who are 18 years and older, although most people having abdominal surgery tend to be older than 60 years [88-90]. Height, weight and body mass index (BMI) need to be integrated into the model, as these measures vary between individuals and may impact prehabilitation outcomes. Choosing critical descriptive parameters of subjects has been shown to assist in assessing the system operation and grouping precision when engineering a monitoring system [28]. In addition, activity recognition and sensor placement are considered to be important components of a cyber physical system for prehabilitation, as wearable body sensor technology that can accurately and reliably detect the type and intensity of activity performed during the prehabilitation period can provide clinicians with important information on patient progress throughout the programme.

Prehabilitation programmes for patients about to undergo abdominal surgery typically involve primarily aerobic exercise, and, to a lesser extent, strength activity. Wearable devices identify attributes of physical activities via the motion analysis of body segment(s). Each type of physical activity has specific motion characteristics [91]. Recently, wearable sensor technology has been used to develop several datasets that can identify specific human activities [92]. These datasets have used a variety of sampling rates, a number of activity categories, and data from sensors in different body locations to assess human activity and function [93]. The position of the wearable sensor affects the precision of defining the kind of activity conducted. Figure 2.2 depicts the positions where wearable sensors are placed on different parts of the body.

2.3.1 Recognising Activities Using a Single Sensor

Recognising human movement with a single sensor placed on the human body has become increasingly popular over the last decade. Numerous researchers have demonstrated the ability of a single 3D accelerometer sensor to recognise a variety of human movements [94-96]. Karantonis et al. [97] and Mathie et al. [98] placed a 3D accelerometer sensor on the trunks of young healthy people and determined the fundamental action of walking, as well as simulating collapsing, posing, standing and lying in the lab. They had precision of 90.8%, and the system effectively differentiated between an action period and rest. This technique was based on identifying movement via a signal from a 3D accelerometer and using a fast Fourier transformation method to detect the frequency components of the signal. The 3D accelerometer was found to be less accurate for detecting activity in older people, as it showed lower precision when selecting (± 10g) accelerometer sensitivity than the (± 2g) accelerometer sensitivity. In another study, Yang et al. [99] determined that a 3D accelerometer sensor located on the wrist had 95% precision for identifying routine activities including walking, running and standing, through demarcating dynamic exercises from static ones. A multilayer neural learning system was used to determine the differences between static and dynamic exercises. Garcia-Ceja et al. [100] employed a wristwatch accelerometer to detect walking and running. They presented precision values ranging from 60% to 71%, indicating this method had limited accuracy for these two activities.

Sukor et al. [101] used a smartphone accelerometer placed on the participant's ankle for activity recognition. In this study, six activities were selected. These were standing (STD), sitting (SIT), lying (LYI), stairs ascent (STU), stairs descent (STN), and walking (WAL). These activities were chosen because they exemplified the most common body movements in the daily lives of humans [101]. The features of the signal were chosen depending on the time and frequency domain. The principal component analysis (PCA) method was then employed to eliminate the dimensionality of the features and extract the most significant ones that could classify human activities. Results indicated that the PCA-based traits had a higher recognition rate, whereas frequency-domain features possessed a higher precision of 96.11% compared to 92.10% using PCA.

2.3.2 Recognising Activities Using Multi Sensors

This section discusses the recruitment of several sensors for human movement identification. Motion sensors were placed on various areas of the human body to determine the most accurate techniques for recognising human movement [102] (Figure 2.1 below). Parkka [103] put sensors on the wrist and chest of 16 healthy volunteers who carried out four fundamental activities (lying, sitting, walking and cycling). They reported a mean precision of 83% for these activities. Nevertheless, this experiment was conducted in a lab environment, and the wearable sensors were large and heavy (dimensions: 40 cm × 30 cm × 10 cm, weighing up to 5 kg when used with support equipment). Olguın [104] employed three accelerometer sensors on the wrist, chest, and hip to identify sitting, running, walking, standing and lying. The researcher used three subjects in his study. The mean precision detected by the sensor placed on the wrist was 65% for walking, whereas the sensor on the hip played a crucial function in determining activities such as sitting (70%) and running (97%). The sensor on the chest had the highest precision for determining standing (77%). Caution should be taken when interpreting these results, as the subjects performed operations of "sitting, running, walking, and standing sequentially, and no detailed record on the specifics of the data collection was given." Yeoh et al. [105] used accelerometer sensors to detect sitting, lying, standing and walking. Two sensors were put on each thigh and one sensor on the waist of five human subjects. Acceleration data were converted to angular data for the trunk and thigh. Precision was 100% for all activities. The disadvantage of this procedure is that the utilisation of multiple sensor attachments may be impractical during prehabilitation exercises. Chamroukhi et al. [106] assessed the impact of sensors placed in different locations on the body. The combined precision for determining stair ascent and descent, walking, sitting and standing from sensors attached to the chest, thigh and ankle was 90%. However, there was no clear explanation of how data were collected, and the authors did not evaluate the feasibility of applying many sensors to the patient.

Dong et al. [107] employed three sensors positioned on the wrist, thigh and ankle of healthy subjects to detect 14 human activities that were similar to those currently used in cancer prehabilitation programmes (Table 3). These activities included lying down, sitting reclined, sitting up straight, standing, slow and fast walking, jogging, climbing stairs, riding a bike fast and slowly, sweeping, jumping jacks, squatting, and bicep curls. They concluded that the combined data from ankle and wrist accelerometers gave 96.20% precision, which was similar to the 96.95% precision acquired when all three sensors were in use. However, when just one sensor was employed, the precision decreased significantly. For example, when the sensor on the thigh was removed, the detection precision for dynamic everyday activities was reduced to 78.3%, and data from a single sensor located on the ankle was unable to distinguish between standing and sitting up straight.

Decreased detection precision could be attributed to the fact that when just one sensor is employed on the lower limb, there is difficulty distinguishing different activities that may have a similar position for a particular segment (for example, the ankle position in standing and sitting). Despite these limitations, a single sensor located on the lower limb was more precise at detecting activities than a single sensor placed on the wrist, implying that a device placed on the leg was more precise at identifying a greater range of activities than one placed on an upper limb (Table 3). Table 3 shows the sensor position and the detection precision of a specific activity.

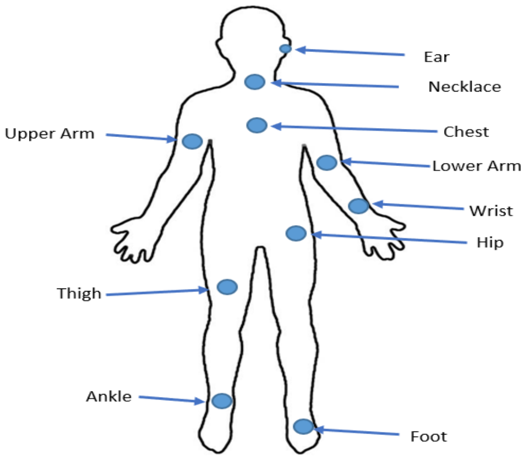


Figure 2.1 Locations of sensors on different parts of the human body.

Table 3. The location of sensors and the associated recognition precision of a specific activity.

Reference	Placement of Accelerometers	Detected Activities	Mean (%) of Grouping Precision
Karantonis et al.[97]	Waist	walking, sitting, standing	91%
Yang et al.[99]	Wrist	walking, running, scrubbing, standing, working at a PC	95%
Garcia-Ceja et al.[100]	Wrist	walking, running	60%, 71%
Sukor et al. [101]	Ankle	6 human activities*	92%-96%
Parkka.[103]	Wrist, Chest	lying, sitting, walking, cycling	83.30%
Olguin.[104]	Wrist, Chest, Hip	sitting, running, walking, standing	65%, 70%, 97%, 77%
Yeoh et al.[105]	Thigh, Waist	sitting, lying, standing, walking	100%

Chamroukhi et al.[106]	Chest, Thigh, Ankle	stairs ascent and descent, walking, sitting, standing	90%
Dong, et al.[107]	Ankle and Thigh	14 human activities**	89.6%
Dong, et al.[107]	Ankle and Wrist	14 human activities**	96.2%
Dong, et al.[107]	Thigh and Wrist	14 human activities**	91.0%
Dong, et al.[107]	Ankle	14 human activities**	78.3%
Dong, et al.[107]	Thigh	14 human activities**	76.0%
Dong, et al.[107]	Wrist	14 human activities**	71.5%

*(STD, SIT, LYI, STU, STN, and WAL)
**(i.e., lying down, sitting reclined, sitting up straight, standing, walking fast and slowly, jogging, climbing stairs, riding a bike fast and slowly, sweeping, jumping jacks, squatting, and bicep curls).

2.4 Activity Detection Techniques

As technology advances, conventional healthcare systems should be modified to provide users with flexibility. The recording of the duration, frequency and intensity of exercise activity, and the surveillance of cancer patients' engagement in a prehabilitation programme may present valuable data for their progression throughout the programme and surgical prognosis [108]. Current research that focuses on identifying and grouping daily activities of people uses either visual observation (most studies) or accelerometer-based systems. Visual aids are used to offer feedback on posture and movement information in vision-based systems. However, these systems are prohibitively expensive and inherently restrict the user's mobility. Accelerometer-based systems that utilise wireless device networks typically provide the user with greater flexibility of movement and are significantly less expensive than visual systems.

Many studies have used a variety of techniques to define features of human physical activities. Time-domain and frequency-domain feature data analysis in accelerometry are the most extensively used data retrieval techniques. Time-domain feature analysis retrieves basic waveform traits of the accelerometry signal, as depicted in Table 4. The analysis of time domain features does not require lag statistics, allowing results to be easily derived from raw data [52]. Frequency domain feature analysis utilises procedures such as Fourier transformation coefficients to determine the signal's periodicity and structure [52]. Frequency-domain analysis typically analyses periodicity components of acceleration data and is employed to extract the dominant frequency components of different activities. For example, the dominant frequency of accelerometry data during slow walking will be less than when walking fast. On the other hand, fast Fourier transformation (FFT) component magnitudes of the signal are assumed to discriminate between activities with similar energy values and are also proposed to extract primary information from the data, reducing data size. Typically, human daily activities, including physical exercise, occur at a frequency lower than 20 Hz [41]. Therefore, frequency-domain features such as the dominant frequency and its magnitude (power), can be extracted from raw acceleration data obtained from sensors to distinguish between different activities and the intensity at which they are performed.

Table 4. Time and frequency-domain features.

Type of Feature	Method
Time-domain	Min, Max, Mean, Standard Deviation, Signal Magnitude Area (SMA), Signal Vector Magnitude (SVM), Tilt Angle
Frequency-domain	Power Spectral Density (PSD), Signal Entropy, Spectral Energy

Consequently, raw sensor data are retrieved and assessed by employing frequency domain features to describe specific activities.

A number of researchers have employed frequency analysis to detect various types of walking at different velocities (intensities). Pachi [109] recorded 800 accelerometer measurements of males and females across various age groups, walking at speeds ranging from 4.5 to 5.2 km/h, and reported the dominant frequency in the range of 1.4 to 2.1 Hz. Sharma et al. [108] calculated the frequency range of three activities (rest, walking and running) in two subjects, carrying a 3D wearable accelerometer sensor attached to their chest. The normalised FFT was then checked for the range of frequencies and the peak magnitude of the dominant frequency. The dominant frequency for rest was 0.5 Hz and ranged from 1.5 to 2.5 Hz. The dominant frequency for "normal" self-paced walking was 2.5 Hz, whereas it changed to 4 Hz when running. Mathie et al. [110] conducted 283 tests by employing a waist-mounted 3D accelerometer and found that the frequency range for various types of walking was from 0.7 (very slow walking, less than 1m/s) to 3 Hz (running). Gaile et al. [111] investigated the frequency components of ascending and descending stairs, utilising a 3D accelerometer sensor. The dominant frequency was 0.9 Hz for ascending stairs, while it was 2.4 Hz for descending stairs. Another study reported the frequency range values between 1.65 Hz for walking downstairs and 3.3 Hz for running downstairs for a subject walking down a staircase [112]. P. Li et al. [113] employed an accelerometer incorporated into a smartphone to determine the frequency components of cycling by placing smartphones on various body sites (chest, ankle and wrist). They found that the frequency component of the accelerometer signal was less than 2.75 Hz while cycling at 100 rpm and was between 1.25 Hz and 1.75 Hz when cycling at 70 RPM. However, the frequency domain for many activities such as rowing, step ups, and cross trainer has not received adequate attention. In summary, most literature indicates that the most common frequency components of prehabilitation physical activities were in the range of 0.25 to 3.5 Hz [46].

The sampling frequency is also a crucial variable in all signal processing applications detecting human activities of daily living (ADL), as it substantially affects the power of the signal, computational load, and performance. The raw sensor sampling frequency was judged to be higher than needed in several studies. For instance, the sampling rate in the work of Yang et al. [99] was 100 Hz. However, such a high rate is unnecessary for the elderly in terms of measuring ADL because the main frequency components of body movement are less than 10 Hz during daily activities [97, 114]. Gao et al. [102] explored the relationship between sampling frequency and recognition rate, and suggested a 20 Hz sampling frequency for multi-sensor systems and a slightly higher value of 50 Hz for single-sensor systems. Maurer et al. [115] also demonstrated that no substantial improvement was evident in the recognition of activities when the sample rate was above 20 Hz. Other researchers, including Khan et al. [116] and Yang et al. [116] have employed a 20 Hz sampling rate for accelerometry data acquisition.

Other vital techniques were using for the activity recognition and healthcare application are Machine learning (ML) and Deep learning (DL). The potential of ML models for healthcare applications is also being boosted by advancements in concomitantly advancing technologies such as cloud/edge computing, mobile communication, and big data technology [117]. Machine learning and Deep Learning (ML/DL), when combined with these technologies, can produce highly accurate predictive outcomes and facilitate human-centered intelligent solutions [118]. With additional benefits such as enabling remote healthcare services for rural and low-income areas, these technologies have the potential to play a critical role in revitalizing the healthcare industry. For example, a smart healthcare monitoring system using sensor fusion and deep learning techniques in heart disease prediction has been proposed and implemented by the authors in [119]. The experimental results show 98.5% of precision in terms of recognizing the disease, which is greater than that of existing state-of-the-art systems. This demonstrates that implementing machine learning techniques could improve the system's classification and make it more seamless in managing large amounts of unstructured healthcare data. However, in this study a special intuitive and logical approached has been applied for filtering the outliers of movement recognition. This to minimize the error delivered by the approached used based on the FFT components outcome of Amplitude (A) and Frequency (F).

2.5. General Scheme of the Sensor Used for Measuring Daily Human Activity

Small, relatively inexpensive, commercially available wearable sensors have been rapidly adopted in mainstream sports for the objective quantification of training volume. Sensor units usually use accelerometry technology to assess movement volumes and provide an approximation of the metabolic demands of specific sporting activities [120, 121]. Specific movement tasks are determined using inertial measurement units (IMU), integrating accelerometers, gyroscopes and magnetometers, which include multiple sensor outputs to identify specific movement tasks. Accelerometers follow the rate of change in velocity via linear acceleration, while gyroscopes appraise orientation and angular speed. Magnetometers supply directional data, similar to a compass, based on the measurement of the magnetic field strength [122].

The use of accelerometer sensors to detect human activity has significant potential because the sensors consume little power, allowing continuous sensing throughout a day [123]. The number of sensors is critical. Using multiple sensors has led to the problem of movement obstruction and reduced functionality when worn over an extended period [124]. Moreover, the inclusion of additional sensors will also increase the cost. To this end, more researchers are applying activity detection approaches where a single accelerometer sensor is used to detect body movement during a variety of activities [125, 126].

There are several issues related to the activity detection approaches using accelerometer sensors. These include rapid and accurate data processing, the development of feature extraction methods, and high-performance classification support techniques [127]. For instance, if the features are not appropriately extracted from the raw signal, there is a decrease in the preciseness of activity detection and a reduction in the computational effectiveness. Many studies have implemented feature extraction methods to select the most crucial features grouping human activities [126, 128, 129]. Moreover, the dimensionality reduction process may also be implemented to decrease the dimensionality of raw data and transform original traits into a decreased dimensional space [127]. These processes must fulfil several requirements, including high precision, short training time and real-time data generalisation [130].

2.6 Summary

Supervised and unsupervised exercise programmes are the two most common prehabilitation interventions that are recommended for abdominal cancer patients awaiting surgery. Each programme has advantages as well as drawbacks. For instance, the crucial advantage of a supervised programme is that the patient is under the direct supervision of a physiotherapist or clinician while performing physical exercises, enabling direct control of the type and intensity of the prescribed physical activities. However, higher healthcare costs, limited capacity of health facilities in terms of equipment and personnel, and the need for patients to travel to sites where the facility is situated are the main issues related to this approach. The low cost and flexibility associated with unsupervised programmes give patients the opportunity to engage in prehabilitation activities in their home and community environments. Nevertheless, in unsupervised programmes, it is difficult to determine whether the patient is performing the physical activities as prescribed. There may also be inconsistencies in conveying information between the clinician and patient, and there are challenges related to recording and updating progress.

The mixed mode prehabilitation model with remote monitoring offers a solution to address the disadvantages of supervised and unsupervised models. The essential notion of a mixed mode model is to encapsulate the advantages of both programmes, while minimising their drawbacks. Wearable devices have the potential to detect and provide feedback on exercise behavior throughout the prehabilitation period. However, it is crucial that these devices can detect the parameters of specific activities that are prescribed by the clinician. These parameters include the type (mode), duration, frequency, and intensity of the activity, and the length of time of the exercise intervention. Moreover, the ability to detect non-prescribed activities and inactivity (idleness) can provide additional information on levels of activity engagement throughout the prehabilitation period.

In general, several countries face severe shortages of healthcare staff, resulting in a decline in medical care quality and a significant increase in healthcare expenses. Many healthcare applications, such as remote monitoring of vital signs (temperature, blood pressure, etc.), are currently being developed using the IoT and CPS. In addition, the utilisation of IoT and CPS techniques may be able to overcome a variety of obstacles, including geographic distance and a lack of healthcare resources and facilities. As a result, CPS could be the best solution for the remote monitoring of cancer patients who are involved in a mixed mode prehabilitation model.

Chapter 3 Modeling and Development Tools

3.0 Introduction

The evaluation of the simulation of different physical activities in real life scenarios offers succinct explanations and suggestions to develop an optimal support of the mixed prehabilitation program for the cancer patient. In addition, an efficient design of the cyber physical system can accurately identify and provide feedback for patients and clinicians on the type and intensity of activities preformed during patient's prehabilitation. The major instruments and materials engaged in this study are discussed in the following sections.

This chapter discusses the broad range of tools and resources employed in this study to build and test the notion of mixed mode prehabilitation system and develop the "cyber-physical system for cancer patient prehabilitation" model. These tools and materials enable building models representing real-life scenarios and simulate various events to derive meaning and draw conclusions from data obtained. Section 3.1 discusses the role of the wearable sensor device and different supporting bords such as (real time clock and SD boards) that perform with the wearable sensor. Then, in Section 3.2, we discussed the supporting software for the preliminary and advanced data analysis during different design stages. In section 3.3, we discussed the role of current consumption management for the wearable sensor device. The role of the Raspberry Pi as a gateway and its support for embedded codes has been discussed in section 3.4. The cloud and supported platforms are discussed in section 3.5. In section 3.6, the physical fitness tools that were recruited during this research have been illustrated. Section 3.7 demonstrates the chapter summary.

3.1 Wearable Sensor Device

Wearable devices are now used for a variety of healthcare monitoring tasks. The sensor is one of the most important elements in data collection. In particular, to accurately observe motion of the human body, 3-axis accelerometer sensors obtain data and can be used for human activity recognition in the ubiquitous computing domain as well [131]. Wearable devices, in specific, are becoming increasingly important for long-term health monitoring as the world's elderly population grows. As a result, many people are looking for alternatives, such as a device that can be worn on the body that not only continuously monitors the user's health in real time but also provides timely insights on various health parameters to both the user and his or her physician [132].

In chapter 2 it was highlighted that several instruments can be utilized as wearable sensors to detect human activity. The developed wearable sensor used in this study is based on the Microduino technology.

Its preference over other devices can be attributed to the software and hardware modularity and flexibility in stacking components. Designs of various functional boards have open-source software for the commercially available hardware used for development. The system is also cost-effective but still has a key feature of more expensive sensors such as the number of sensor nodes, making it suitable for several environmental monitoring applications. A combination of the Motion Sensor (10-DOF), the SD board and the transmitter (NRF24), along with the real-time clock (RTC-PCF8563) and microcontroller (Core rf128), forms the basic structure of each sensor node. Further information about each of these products is described below. Below discussions are in two directions: first, describe the functionality and ability of different Microduino bords while in the second direction the examples are demonstrated of WSD and its role in this research.

1. Microduino-Motion (Microduino-10-DOF)

The Microduino-10DOF consists of four sensors with one 3-axle gyroscope (MPU6050) and one 3-axis accelerometer sensor (MPU5882), one sensor of magnetic field (HMC5883L) and one digital barometer (BMP180) [1] (Figure 3.2a). The initial step of the remote surveillance of physical activity is to collect the raw 3-d acceleration data using the wearable sensor method (X-axis, Y-axis, and Z-axis). The collection and processing of raw data from the accelerometer has been previously described in Chapter 2, sections 2.3.1 and 2.3.2. Figure 3.1 shows 3D (X-axis, Y-axis, Z-axis) raw accelerometer data captured from MPU6050. There are four acceleration ranges (±2 g, ±4 g, ±8 g, ±16 g) on the MPU6050 3D-accelerometer with variable ranges of sensitivity that range from ±2 g, which is regarded as highly sensitive to than ±4 g, which is better able to detect larger accelerations. The sampling frequency band of the MPU6050 is 1Hz - 1KHz [2], allowing the sensor to capture human physical work with great precision [1]. The aim of recruiting MPU6050 is to capture the patient's different movement types, such as physical activity or daily living activity. The majority of abdominal patients are elderly people (> 65 years of age). Accordingly, ±2 g sensitivity has been selected with a 128 Hz sampling frequency [3, 4].

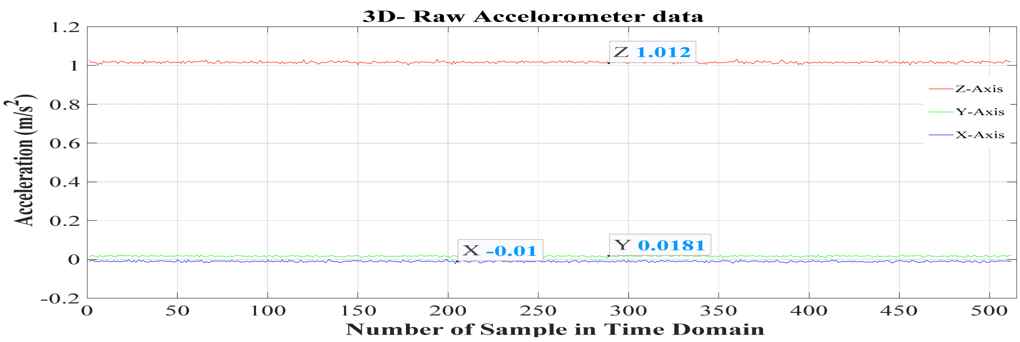


Figure 3.1 3D -Raw accelerometer data captured from MPU6050 sensor.

2. Microcontroller (Core rf128)

The Microduino core rf128 processor supports computation and interaction by integrating a wireless protocol of 802.15.4 and enabling several wireless components like Zigbee, MAC/6LoWPAN and RF4CE (Figure 3.2b). The Microduino's modest operational efficiency, open-source structure, stickability and cost-effective features, along with an inbuilt clock of 8 MHz Frequency and 2K RAM capacity, make it preferable for the study [133]. The Core rf128 processor is designed to monitor and manage every different WSD transaction. These include data flow management such as (initialize the variable iteration, set the timer size, create the timestamp for the current reading), short- term information storage (gathering the data from the accelerometer and stored in temporary variables (tempx,tempy,tempz)), data processing data such as DC offset raw filtered 3D accelerometer data. Figure 3.3 shows a 4 sec sample of DC offset filtered data. Control and data transmission to the higher level's payload is prepared containing necessary information like (node ID, count, amplitude, and frequency).

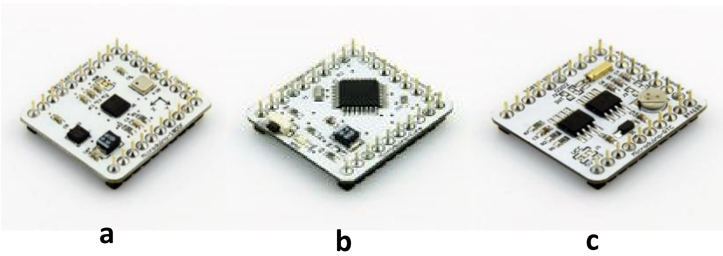


Figure 3.2 a. 10-DOF, **b.** Core rf128, and **c.** RTC (PCF8563)

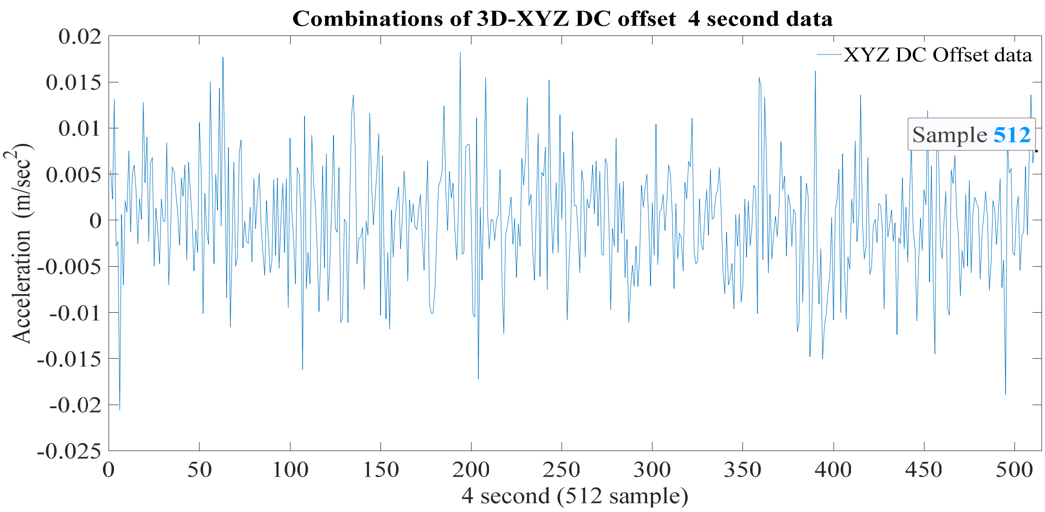


Figure 3.3 Shows 4 second 3D- XYZ DC filtered data

3. Real-Time Clock (RTC)

The timestamp holds a critical significance in every element of the IoT system, because it is important to monitor the date and time features throughout the prehabilitation programme. A time pointer is required to mark the beginning and finishing stages of physical activities. A timestamp is also required for validation, analysis and exploration of long-term stored data. Figure 3.2c shows the Real-Time Clock board (RTC) PCF8563 that was designated to be a component of the WSD for the production of a date and time stamp for gaining real-time data (Figure 3.2c).

4. SD-Board

The SD board and the sensor node have been attached together for storing the data [4] (Figure 3.4a). A SD card is used in the wearable tool for prolonged storage of raw and refined data. The SD card attached with SD board design can be utilised for long durations (up to 240 hours, for 16GB storage card) to retain uninterrupted raw data of accelerometer inputs. In addition, long-term storage of data enables academic researchers and health care providers who work with cancer patients to conduct additional research and investigations.

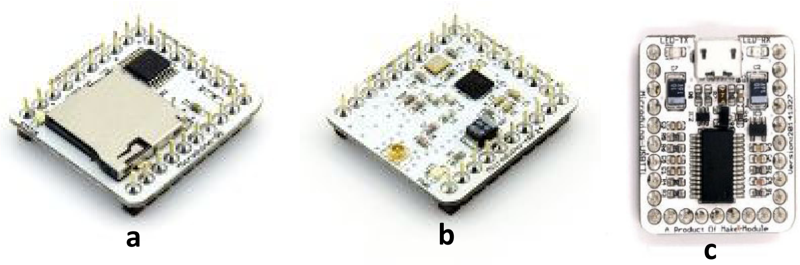


Figure 3.4 a. SD board, **b.** NRF24, and **c.** USB TTL interfacing board

5. NRF24l01

As indicated in Figure 3.4b, a Nordic nrf24 chipset is used for the transmission and receipt of data packets. It runs on an upgraded ShockBurst protocol and is suited for ultra-low-power wireless applications with three voltage data rates of 250kbps, 1Mbps and 2Mbps [134]. The chipset has a low volume and a low rate of data transfer, allowing the data transmission in the current study to occur every 4 seconds, a data rate of 250kbps (as receptor sensitivity is -93dBm at 250kbps, and drop to -82dBm at 2Mbps). The Nordic nrf24 supplies 125 channels (2.4-2.525 GHz) occupying a bandwidth lower than 1MHz, thus enabling the module for simultaneous utilisation of 125 channels, which in turn facilitates a network of 125 stand-alone modems [135]. Another feature of the nrf24 transceiver shown in Figure 3.4, is that uses a packet structure known as Enhanced ShockBurst, that is segmented into five separate sections. The recently launched Packet Control

Field (PCF) is employed by the Enhanced Stock Burst for better interaction capabilities with a restricted preamble, address, payload and Redundancy Control (CRC) factors of Shock Burst (Figure 3.5) [7].

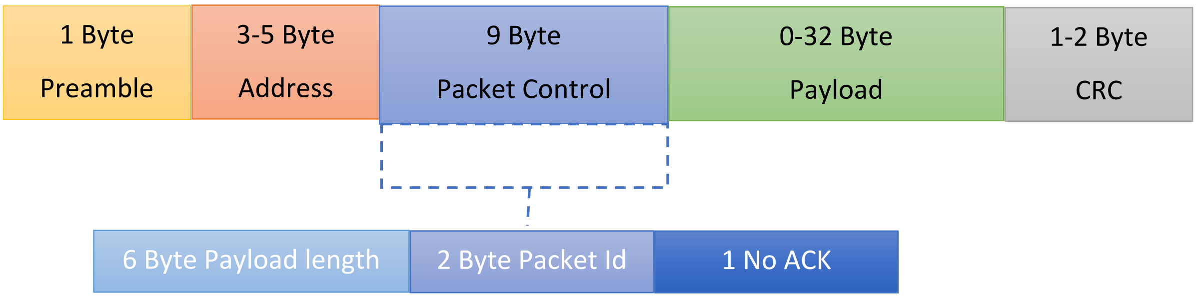
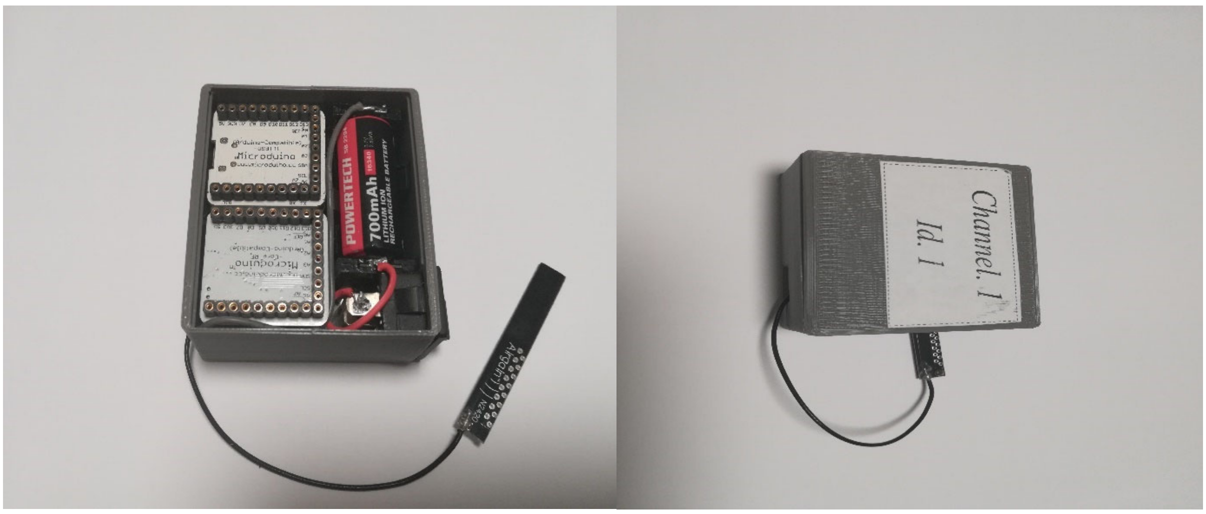


Figure 3.5. nrf24 Enhanced ShockBurst packet structure.

6. USB TTL

The USB-TTL is an interface chip facilitating conversion that can translate from USB to serial UART or synchronous/asynchronous Bit-Bang interface mode. FTDI offers driving applications for multiple operating systems available. Well-designed and convenient, the Microduino-USB-TTL exhibits compatibility with Arduino, which is demonstrated in Figure 3.4c [8]. The USB TTL module board is a separate entity from WSD and can be detached from the stacking boards of Microduino combination modules after the downloading of integrated operation code.

Finally, WSD has been constrained and packed in a single 3D printed box as illustrated in Figures 3.6 a and b as a result of the above Microduino combo boards. Furthermore, a custom-made band was used to secure the WSD on the ankle of the patient.



Figures 3.6 a. Shows the combinations of Microduino bords with 3.7DC battery, **b.** Final WSD inside 3D printed box.

3.2 WSD Embedded test software environment

Wearable systems for patients' remote monitoring consist of three main building blocks: First, the sensing and data collection hardware to collect physiological and movement data. Second, the communication hardware and software to relay data to upper level. Finally, third blocks are the data analysis techniques to extract relevant information gathered from different sensors.

Hardware bords were used to construct the WSD model, as was previously mentioned in the preceding section. Arduino Integrated Development Environment (IDE), and embedded language both are the core to enable the WSD to execute the sensing function. The IDE simplifies the process of writing code and uploading it to the board. The Microduino is congruous with the integrated code due to a built-in C-type language structure. Embedded software played an important role in developing the WSD features and functionality. For example, at the early stage of designing and implementing the WSD, system, it has the ability to store raw 3D accelerometer data as shown in Figure 3.7 a. An additional feature has been added to enhance the storage data type, such as including date and time stamps, as shown in Figure 3.7 b. In addition, many features could be embedded by using open-source IDE platform based on design concepts and hardware limitation.

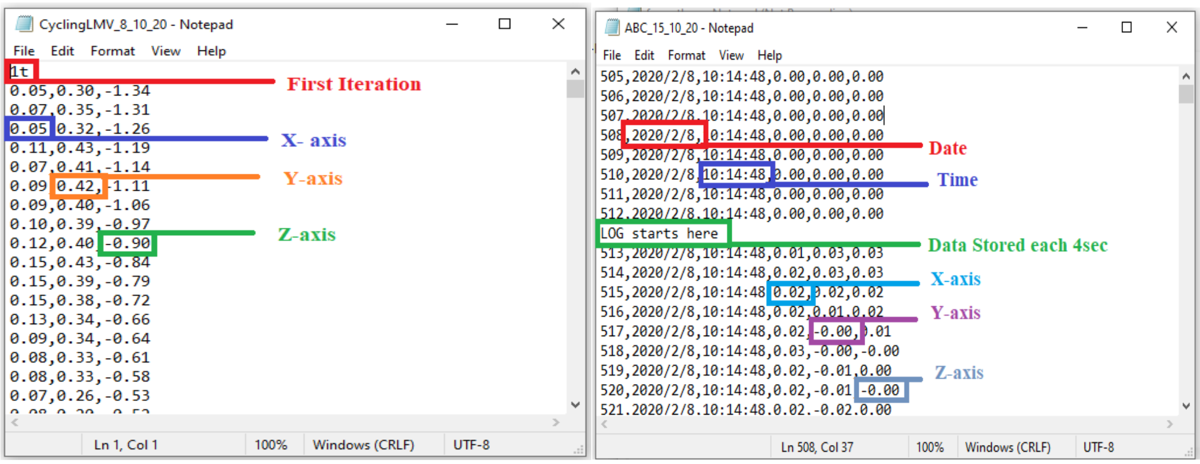


Figure 3.7 a Shows raw XYX data stored only in SD card, **b**. An additional storage features has been added such as date and time stamp.

3.3 WSD Power Management

Different Microduino boards built for the WSD have two main options: idle and operation mode. Two subsections follow that discuss both modes and how programming can benefit from idle mode to reduce total power consumption.

3.3.1 WSD at Operational Mode power and current consumption

The comparison of the equipment in idle as well as completely operational mode enables the examination of energy used by the wearable equipment. The wearable node is driven by a battery of 1⁄2 AA of 700 mAh that is functional at 3.7V with a cut-off voltage of 2.75 V, which is able to power the Microduino hardware that operates on 3.3 V. The battery was chosen on the basis of energy consumption, sensor's dimensions, and the magnitude of the sensor box. Table 3.1 shows all module currents in idle as well as working conditions. The equipment consumes a total of 26.33 mA and 38-44 mA current consumption in inactive and operational modes respectively, while the total power consumption for both conditions is 97.4 mW and 141- 165 mW, respectively.

A small deviation in current typically ranging between 38-44 mA is seen when the data is being transferred or received. This can be attributed to multiple causes like the consumption of extra energy by the SD card during data storage in comparison to its idle stage. Based on estimates shown in the Table 3.1 below, the battery capacity is suitable for constant collection, storage and transmission of data for around 16 hours.

Table 3.1. Current consumption of the components in the WSD.

S. No	Sensing Board	Idle Mode Current(mA)	Operational Mode Current (mA)
1	Core RF	22	22-24
2	10 DOF	0.01	0.02-0.06
3	SD card	1.5	5-7
4	NRF24	2.8	11.3-13.5
5	RTC	0.032	0.05-0.1
Total Current Consumed		**26.3mA**	**38.37-44.66 mA**

3.3.2 Optimized WSD current consumption.

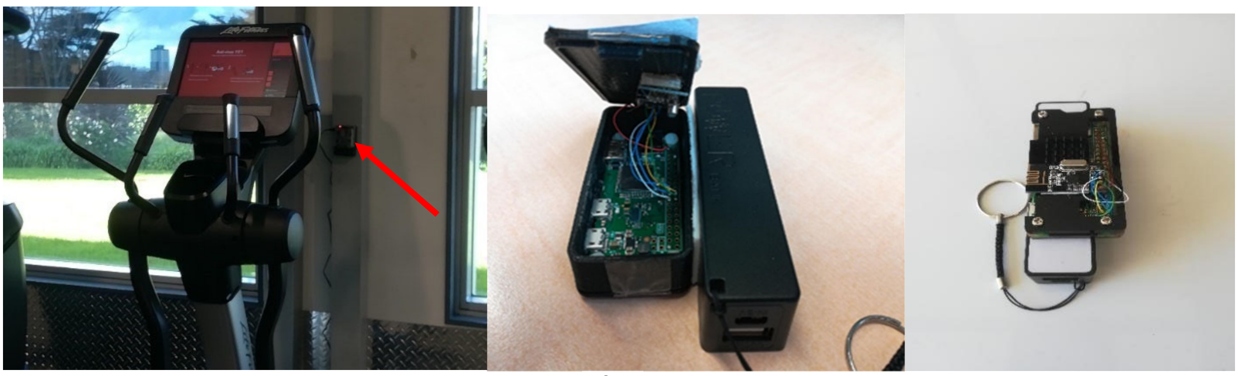
The Microduino boards have one main feature in terms of power management, which is the ability to work in both idle mode and normal operation mode. The current optimization between both modes based on the different WSD operation status boards can significantly reduce the current consumption while the board is not in use. In this study, data was transmitted from WSD via NRF24 every 4 seconds with a one-second transmission time. Accordingly, the NRF24 board goes into idle mode for 45 seconds with current consumption of 2.8 mA only and for 15 seconds with 11.3 mA. The total NRF24 current consumption is 4.925mA. On the other hand, the time storage data of SD card board is 1.5sec every 4 sec, so the active time of SD bord will be 22.5sec each minute and 47.5sec go to the idle mode. Based on that, the total current consumption of the SD board will be, 4.46mA while the idle mode of the other boards does not have large contributions to total current reductions. Accordingly, the total current will be around 31.475 mA, and the battery life will be 22.23 hours. The current optimisation obviously showed 28% increments in battery life operations. However, it is optimal that the battery be recharged each night before the patient goes to sleep via a USB cable.

Table 3.2. Optimized Current consumption of the components in the WSD.

S. No	Sensing Board	Optimized Mode Current(mA)
1	Core RF	22
2	10 DOF	0.03
3	SD card	4.46
4	NRF24	4.925
5	RTC	0.07
Total Current Consumed		**31.475mA**

3.4 Raspberry Pi as a Gateway

Several intelligent technology-based gadgets like smartphones, laptops, iPad, Tablets, and Raspberry Pi are functional in IoT's in the form of edge computing gateways. This study engages two distinct versions of Raspberry Pi, namely Raspberry Pi 3B (RPi3B) in the form of a base station gateway (Figure 3.8 a) and Raspberry Pi Zero W (RPiZW) as a mobile gateway (Figure 3.8 b and c). The primary rationale for adopting RPi3B as an edge base station is because of its integral one-board computer system, which is fully functional with an electronic power supply of 1250MHz at 5V DC, in addition to Wi-Fi and Bluetooth capabilities [9]. The speed of this computer's processor is Quad Core @1250 MHz, with 1GB RAM of 400 MHz SDRAM and micro-SD card having a data storage capacity of 16, 32, 64, and 128GB. It is capable of interfacing with a number of affordable physical or wireless small-sized peripherals.



a b c

Figure 3.8. a. RPi3B as base station gateway, (**b** and **c**). RPiZW as a portable gateway.

These characteristics allow the equipment to manage multiple users of WDS simultaneously without any delay in several facilities such as (e.g., rest home, physiotherapy centre, gymnasium (GYM), or any other comfortable location). Figure 3.9 shows an example of a Raspberry Pi log file for a real-time data storage process. The Raspberry Pi specifications offer an ability to process, organize, and store different data types at the same time.

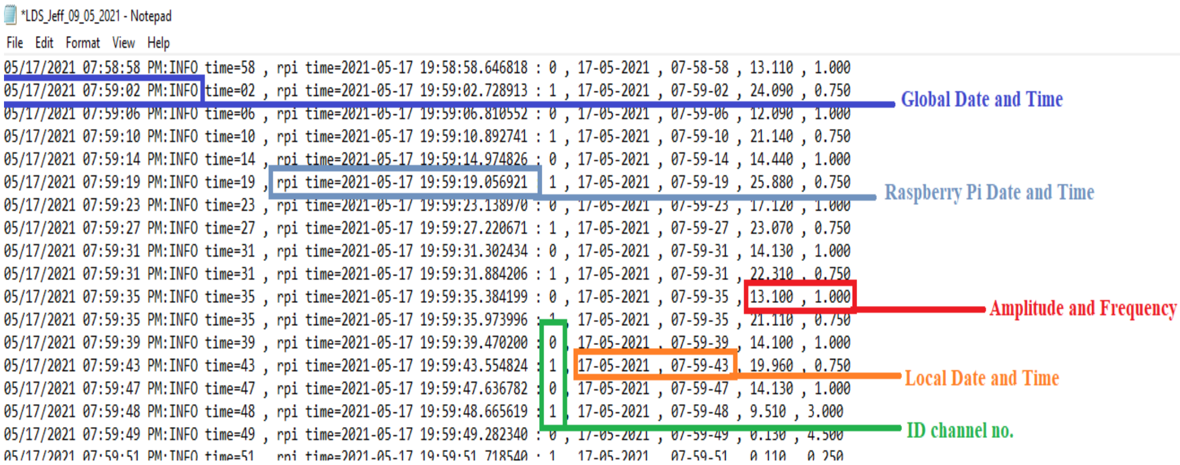


Figure 3.9 Shows an example of a Raspberry Pi log file for a real-time data storage.

Alternatively, the RPiZW is employed as a mobile gateway to process, store and transmit data to the upper level from one or more WSD user. The characteristics of this system resemble those of the RPi3B apart from having 1GHz core of reduced speed, 512MB of RAM storage capacity, being half the size of the RPi3B (65mm x 30mm x 5mm) and having a lower voltage consumption (Table 3.3). Hence, it is very easy for the patient to perform outdoor physical activity or go to a gym along with the RPiZW as a portable gateway for its specifications (light weight, small size, low power consumption). Additionally, the mobile gateway is only requiring a single AA rechargeable battery of 2500mAh and can be operational for 20 hours on the basis of the calculation shown below. A General-Purpose Input/Output (GPIO) port with a nrf24l01 radio module connects the RPi3B and RPiZW to the WSD’s during the transmittance and reception of data between multiple WSDs and gateway.

Battery life of RPiZW = 2500 mAh/120mA = 20.833 ≈ 20 hours

Table 3.3. RPiZW current and power consumption in idle and operational modes.

RPiZW	Current Consumption (mA)	Power Consumption (W)
Idell mode	80 mA	0.4 W
100% CPU load	120 mA	0.7 W
200% CPU load	160 mA	1.1 W

3.6 Internet of Things and ThingSpeak Platform.

The Internet of Things (IoT) has many features that could significantly supported the Cyber physical system for remote monitoring and interacting with the prehabilitation program. Figure 3.10 shows the common features of IoT that may cover the proposed system requirements in terms of connectivity, analysis, active engagements, scalability, and artificial intelligence [136]. The connectivity is the most critical feature of the Internet of Things. Without flawless communication among the interconnected components or objects, the IoT ecosystem (sensors, compute engines, data hubs, and so on) cannot function properly [137]. Furthermore, analysing is very important to extract knowledge from the generated data. In addition, multiple products, cross-platform technologies, and services collaborate on an active engagement basis via IoT [138]. Moreover, the scalability and artificial intelligence both are important IoT features in terms of amount of data generated from different connected devices and of enhancing the data processing and analysis by applying different neural techniques [138].

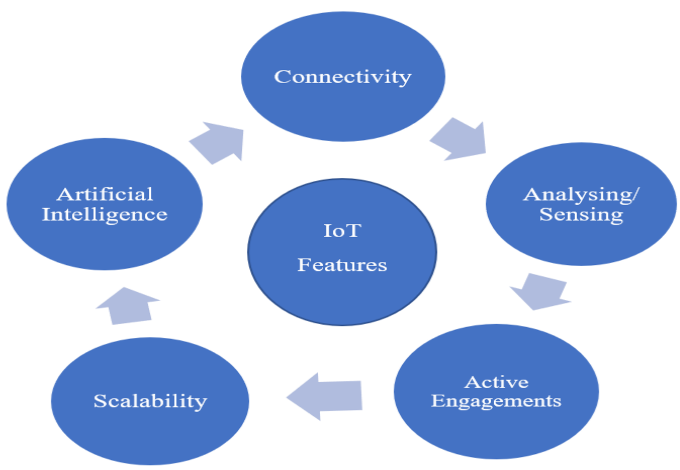


Figure 3.10 Shows IoT main features that could support the prehabilitation program.

The ThingSpeak (TS) platform may cover the above requirements. In terms of connectivity, the Internet-Cloud layer consists of numerous features and is represented by communication protocols such as HTTP and MQTT that can be used to acquire data frames from the gateway or edge device. The different computing methods such as digital signal processing, artificial intelligence, and machine learning-based approaches could be used at various levels by exploiting MATLAB software which is among the main supporting tools for the TS platform [139]. On the other side, the TS has its own data repository that may be used for long-term storing of patient activity movement data or any other type of relevant knowledge that can be easily handled. Accordingly, the TS has been employed in this study to meet IoT criteria for remote control of the prehabilitation programme. In addition, the TS platform can facilitate users to perform multiple activities by integrating with online services, social media, and Application Programming Interfaces (API). For example, applications that can be integrated into this platform include: ThingTweet app for tweeting notifications and messages; TweetControl app for responding via triggering words; TimeControl app for scheduling particular actions; React app to perform certain activities upon meeting criteria; Talkback app for sending a command to equipment; and ThingHTTP app for interacting with different online services and APIs [11].

TS's principal component is its data storage channel and the ability to accumulate data from different devices. Up to eight parameters, including device location and URL, can be saved for each channel. The channel can be released to other users or private users by facilitating them with an API key to access the data. However, for selective specified individuals, the private channel can also be extended.

3.5 Physical Fitness Tools

As described in Chapter 2, sections 2.2 and 2.3, one of the key elements of supervised or unsupervised prehabilitation programmes are the type of physical exercise undertaken during the period of prehabilitation. The patient participating in the prehabilitation program can do either one or more of the commonly prescribed nine physical exercises (CY, TM, CT, RO, LP, STAD, SP, W, RU). The physical fitness equipment of the physiotherapy laboratory and Central University GYM facility shown in Figure 3.11 are accessible to the patients and the healthy participants during the prehabilitation program. The basic data of every activity was appropriately recorded for a diverse group of patients and healthy participants of variable age groups. The key benefit of using common types of fitness equipment by multiple subjects was that findings could be validated using the same piece of equipment as a reference.

a

b

c

d

e

f

Figures 3.11 a. Stationary cycling, **b.** Treadmill, **c.** Cross Trainer, **d.** Rowing, **e.** Leg press, f. Step Up

3.6 Summary

This chapter discussed the cyber physical system components, underlying software, platform, and physical fitness tools that can be used to support a mixed mode prehabilitation programme. To enable the mixed mode prehabilitation programme, the cyber physical system must be capable of connecting, sensing, and collecting meaningful information. To accomplish this objective, numerous steps have been taken, including the use of open-source development boards (Microduino), as well as low power consumption boards that extend the life of the sensing device's battery and extend the network's lifetime.

Long-term storage capabilities enable continuous storage of raw and processed WSD data for more than ten days on a 16GB SD card. These data provide long-term storage that can be used for offline data processing and independent research. On the other hand, an unlicensed spectrum communication band (2.4-2.55GHz) with various data rates (250Kbps, 1Mbps, and 2Mbps) was employed to secure bidirectional communications between the WSD and the gateway. In addition, two models of the Raspberry Pi have been chosen in this study RPi3B and RPiZW as a base station and mobile gateway, respectively. Small size, low cost, computation power, data storage, and functionality made Raspberry Pi to be chosen over the various types and models of other electronic devices such as laptop, smartphone, and Tablet. The role of the cloud computation is offered by the TS platform in this work. TS can offer long-term data repository, real time visualization and data analysis, handles up to 10 channels simultaneously with eight data fields of each channel. Furthermore, cloud TS data analysis and visualization is based on the MATLAB software which is common tool that academic researchers use. Finally physical fitness tools have been used for individuals' participants (healthy and patient) during the prehabilitation program. The primary advantage of having numerous people use similar types of fitness equipment was that findings could be validated using the same piece of equipment as a reference.

Chapter 4 Concept for mixed mode prehabilitation monitoring model

4.0 Introduction

Cancer patients with low fitness capacity are at greater risk of postoperative complications, longer hospital stays, and mortality [140]. One of the most notable challenges confronting both healthcare providers and patients is to improve the patient's physical fitness within the available duration (four to six weeks) prior to surgery. Supervised and unsupervised prehabilitation programmes involving physical exercise are the most commonly recommended methods for enhancing postoperative outcomes in patients undergoing abdominal surgery. Owing to obstacles such as geographical isolation, many patients have limited access to medical centres and facilities that provide onsite supervised prehabilitation programmes [140].

An approach for addressing resourcing and geographical isolation is to develop a mixed prehabilitation model via remote monitoring that includes components of supervised and unsupervised prehabilitation such as the identification of fundamental parameters of physical activities (type, intensity, frequency, and duration) over time. A mixed home-based with virtual support of prehabilitation programme could be delivered through a cyber physical system. This may have the potential to minimise the inequities for patients who cannot access high-quality supervised prehabilitation and potentially reduce the burden on the healthcare system [141]. Such an approach could enable cancer patients to perform prescribed physical activities in their communities without the need for regularly visiting a hospital or physiotherapy centres. The healthcare staff could also be provided with online tools for monitoring patient progress remotely. The tracking of patient progress in prehabilitation could be made through a mathematical model that works out the credit of the efforts made throughout the program. Patients should have the flexibility of using both personal, public and/or specialized facilities. The unique feature of this model is the real-time feedback of the specific type of prehabilitation activities undertaken by the patient and the quantification of exercise intensity and duration. Thus, a mixed model has the potential to reduce the impact on the healthcare system whilst providing cancer patients with the opportunity to partake in prehabilitation in their local community under remote monitoring and supervision.

4.1 Development of Mixed-Mode Prehabilitation Programme Model

The development of a mixed prehabilitation model requires an understanding of the key parameters of supervised, and unsupervised prehabilitation programmes. The programs are discussed in Chapter 2. Supervised prehabilitation is the most common programme applied in many healthcare centres. One main advantage of this model is the physical presence of medical staff. This assures the patient's compliance with the prescribed physical activities at the required intensity during the prehabilitation programme [90, 142, 143]. The main disadvantages of this traditional model are it demands resources (e.g., physical facilities, such as hospitals and clinics, equipment, and qualified instructors); and it is limited to patients who have geographical access to these resources. In contrast, an unsupervised community-based model of prehabilitation allows patients to perform physical activities in diversified local community settings, including home, gymnasium, and outdoors [34, 144]. Home-based programmes are markedly cheaper to run than hospital programmes because of the reduced demand on resources (e.g., facilities, staff, transport), and there is limited need for travelling. However, this type of programme is usually unsupervised, and medical staff cannot guarantee that the patient performs the prescribed physical exercise at an appropriate intensity, which is considered the main drawback in this model.

Table 4.1. Key prehabilitation elements, boundaries, and rules for the model.

Prehabilitation Elements	Prehabilitation Boundaries	Remarks
Time frame of prehabilitation programme	Four or six weeks	Could be less or more in accordance with the patient's status and surgery scheduled.
Number of sessions per week	Two or more	The patient could take part in any number of sessions according to the health supervisor's guidance.
Threshold duration of physical activity per week	150 minutes of moderate intensity or equivalent	75 minutes of vigorous intensity is considered equal to 150 minutes of moderate intensity [84, 85].
Intensity level	Light, moderate, vigorous	Light < 50% of maximal heart rate, moderate 50%–70% of maximal heart rate, and vigorous 70%–80% of maximal heart rate [81].
Minimum duration of each session	10 minutes or more at a moderate intensity	Five minutes of vigorous is equivalent to 10 minutes of moderate and approximately 15 minutes of light intensity [86, 87].
Physical exercise types	Walking, running, cross-trainer, rowing, treadmill, step-up, leg press, cycling, staircase ascending/descending	This could be any combination of these nine activities and is based on the clinician's recommendations.
Location of the prehabilitation programme	Indoor, gym, outdoor	According to the availability of physical resources and the patient's status.
Negative impact	Bed rest	A whole week of hospitality with no physical activity will be considered bed rest. Each hospitalisation day is considered a (-1) credit point and detected from the total accumulated gain. [88, 89].

The length of a prehabilitation programme for cancer patients ranges from two to eight weeks but is often implemented as four to six weeks [63-66, 68]. Physical activities are the main component of such programmes. A clinician can prescribe the patient one or more of the nine most common types of physical activities, which include walking, running, cycling, treadmill, cross-trainer, step-up, leg press, rowing, and staircase ascending/descending [34, 142, 144-147]. The prescribed exercise intensity, duration, and frequency of prehabilitation programmes vary across the documented studies [146, 147]. However, it has been suggested that the total weekly thresholds should be at least two to five times of physical activity per week of a total of 150 minutes of exercise at a moderate intensity, 75 minutes at a vigorous intensity, or a combination of vigorous and moderate intensity that are equivalent to a similar magnitude of exercise [34, 146, 148, 149]. These target threshold values may be adjusted in accordance with the initial programme parameters prescribed by the clinician. Bed rest or prolonged periods of inactivity are considered to have a negative impact on the prehabilitation programme [150-152].

Extracting the advantages and avoiding the drawback of each prehabilitation model (supervised and unsupervised) lead to forming an innovative mixed prehabilitation model. Table 4.1 encapsulates prehabilitation physical exercise parameters and their boundaries for the mixed mode prehabilitation model. The most noteworthy advantage of this model is that it is flexible and easy to construct because the key element factors and boundaries were attained from studies in the extant literature that have developed supervised and unsupervised prehabilitation programmes for patients with abdominal cancer.

4.2 Mathematical Formula for the Mixed Prehabilitation Programme.

The main objective behind developing a mathematical model is tracking and providing feedback on patient activities during the prehabilitation programme. The unique feature of this model is the real-time feedback of the specific prehabilitation activities undertaken by the patient and the quantification of exercise intensity and duration. This may be made available to the various parties of interest through the cloud-based system. In addition, the prehabilitation mathematical formulas are extracted from the various research findings that were discussed in Chapter 2 and the previous section.

Prescribed physical activity can be performed on any number of days during the week, and all the physical efforts will be accumulated as a credit gain. One credit point will be equivalent to the completion of a physical activity performed at the prescribed duration and intensity on any given day (i.e., 30 minutes of moderate daily activity using any of the standard prescribed activities). Any further efforts beyond the prescribed exercises will be logged as additional credit points. Theoretically, the system continues calculating and accumulating the credit gain for patients performing more exercise than originally prescribed by the clinician. In this model, an assumption states that (two points) are the maximum number of credits gained per day, which is equivalent to approximately 60 minutes of moderate exercise [153] as per Equation (1).

$$P = W_e * I * \left(\frac{D_e}{T}\right) \text{...} (4.1)$$

where:

$\boldsymbol{P}$ is the credit gained while implementing the prehabilitation programme regardless of the duration of the entire programme. Generally, such programmes have a length of four or six weeks. In this study, a six-week prehabilitation programme is used as an example and is represented as P_a for the four weeks program, and P_b for the six weeks program. As a result, the equation will be the same; the only difference will be the number of days (28 or 42, depending on the programme type). Accordingly, the volume of the P values will change according to the patient efforts.

$\boldsymbol{I}$ indicates the exercise intensity level. Here 0.75 is allocated for light intensity, 1 for moderate intensity, and 2 for vigorous intensity. The weighting of the different intensities is based on the relative effect of each intensity on improvement in health and fitness [154-157].

$\boldsymbol{T}$ is the minimum threshold time. This threshold is 10 minutes of physical activity at a moderate or vigorous intensity [158].

$\boldsymbol{D_e}$ is the duration of exercise, which is proportional to the standard unit time $\boldsymbol{T}$. Currently, the system considers and calculates each effort made by the patient regardless of meeting threshold time target (10 minutes at moderate intensity). This is because it is still unclear whether very short bursts of exercise (less than 10 minutes) at a moderate or vigorous intensity should be discarded or not. In the setup system other assumptions could be added such as ignoring any efforts with less than threshold time (10 minutes) if there are discontinuity for more than 1 hour. Another assumption can be to ignore for the exceeding efforts (more than 60 minutes with moderate intensity or equivalent), with a warning message to be sent to the patient.

$\boldsymbol{W_e}$ represents the modality or type of the prescribed physical exercise. At this stage of the model, all nine types of exercises are initially given the same value. The credit value for type of exercise is based on previous studies [34, 148, 149, 159], where the patient must perform 150 minutes of moderate-intensity exercise or equivalent per week (e.g., 30 minutes of moderate physical activity five times per week) for a period of six weeks. In this example, the total impact of exercise over the six weeks, equates to a total of 30 credit points. The exercise intensity *(I)* is one (moderate intensity), the time per session (*De*) is 30 minutes, and the minimum threshold for time (*T*) is 10 minutes. Given that P*, We*, *De*, and *T* are known, Equation (1) can be re-arranged to calculate $\boldsymbol{W_e}$ (see formula below). This would result in $\boldsymbol{W_e}$ being $\mathbf{0.335}$.

$$P = W_e * I * \left(\frac{D_e}{T}\right), 1 = W_e * 1 * \left(\frac{30}{10}\right); \text{ then the value of } W_e = 0.335$$

Future work may differentiate among activities when it comes to weight assignment. The total credits of each programme can be varied in accordance with the programme length, prescribed physical exercises, as well as the duration and frequency of each exercise per week.

As remarked previously, the six-week prehabilitation programme($\boldsymbol{P_b}$), was selected as a case for the implementation of the mathematical formula. The programme duration is six weeks (i.e., 42 days), and the duration of total physical activity suggested here is equivalent to 150 minutes of moderate intensity exercise per week. Theoretically, a 30-minutes physical exercise session at a moderate intensity is equivalent to 1 credit point, as per Equation (1). Therefore, the patient is required to accumulate 30 credit points at the end of the prehabilitation programme (5 points per week for six weeks). The target of 30 credit points provides the patient with a quantifiable goal and gives the therapist an indication of the volume of exercise accumulated throughout the prehabilitation programme. The patient can gain more than the targeted value if he or she is engaged in a more vigorous physical activity than prescribed. In contrast, periods of bed rest reduce the number of prehabilitation credit points. The previous example represents an ideal case, whereas, in reality, the time of physical activity per week, exercise duration, and intensity may vary among patients as per the clinician's recommendations.

The weekly accumulated credit is defined by Equation (2).

$$C_{w_b} = \sum_{n=1}^{7} \boldsymbol{P_b} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4.2)$$

where $\boldsymbol{C_{wb}}$ is the accumulated prehabilitation credits per week. Accordingly, each day has an index, which is represented by $n = 1,2, \ldots .7$.

The total accumulated credit is defined by Equations (3) and (4) below.

$$\boldsymbol{C_T} = \textstyle\sum_{w=1}^{6} \boldsymbol{C_{w_b}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4.3)$$

$$\boldsymbol{G} = \boldsymbol{C_T} + \textstyle\sum_{n=0}^{k} \boldsymbol{R_b} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4.4)$$

where:

$\boldsymbol{C_T}$ is the total accumulated credits for the six weeks without accounting for bed rest.

$\boldsymbol{G}$ is the total accumulated credits with bed rest.

Calculations for $\boldsymbol{R_b}$ (bed rest or hospitalisation) are done by identifying the consecutive days where no activity is detected. The consecutive days of inactivity will be considered after a whole week of no activity due to hospitalisation or another illness. $\boldsymbol{R_b}$ is a constant with a value (-1) and n is the number of days of bed rest or hospitalisation, while $\boldsymbol{k}$ is the maximum number of allowable bed rest days during the prehabilitation programme. It has been suggested that 14 days of bed rest can be deemed sufficient to eliminate the targeted total credits gained during a six-week prehabilitation programme [151]. If this is the case, the patient will need an extended period of prehabilitation to return to the same level of fitness prior to bed rest [151, 160]. The flowchart in Figure 4.1 depicts the key processes of the mixed mode prehabilitation.

The following description exemplifies how the model works practically for a patient walking for 15 minutes at moderate intensity and cycling at a vigorous intensity for 5 minutes. According to our previous records [46, 47], four seconds is the minimum time period for the collection of raw data for movements to be recognised without distortion. Accordingly, the accumulated 225 readings of four-second data epochs were analysed throughout the 15 minutes of walking activity. The same processing was applied to five minutes of vigorous cycling activity. The total credit for each activity is calculated using Equation (1) where:

$P = W_e * I * \left(\frac{D_e}{T}\right)$ = 0.35 * 1*(15/10) = 0.525 credits for the walking activity.

Meanwhile, the credit for five minutes of cycling is 0.35. The total accumulated credits and exercise time for both activities are 0.875 and 20 minutes, respectively. After every 24 hours, the system calculated the accumulated credit gain and time for each recognised activity and then stored this summary information in a separate file.

4.2.1 Database as a Reference

The system is designed to collect, analyse, calculate, and trace human movement data in various states, whether it is physical activity or normal DAL. Based on this, the database in the system will play a significant role in recognizing and calculating effort. Due to patients having different fitness levels and age groups, the basic data related to each physical activity may vary between subjects. Accordingly, the stored database should be managed in a way that helps in system identification and efforts calculation. For example, the personalised database, which is the data collected from the same subject while performing different physical activities, could be a group of data for the same person when he/she is performing the same physical activities at different times. This minimizes recognition errors when the same database is feed into the system as a reference for the same individual involved in the prehabilitation program. Another type of database might be a group database intended for two or more people who have the same results (amplitude and frequency output values are in the nearest range). This type of database includes certain groups based on their age or fitness level. A third type of database can be called a non-personal or shared database, meaning that data is collected from a large number of subjects doing the same physical activity regardless of their fitness level or age group. This type of database is useful for first-time testing where it is difficult for the same person to retest because of physical geography or limited resources.

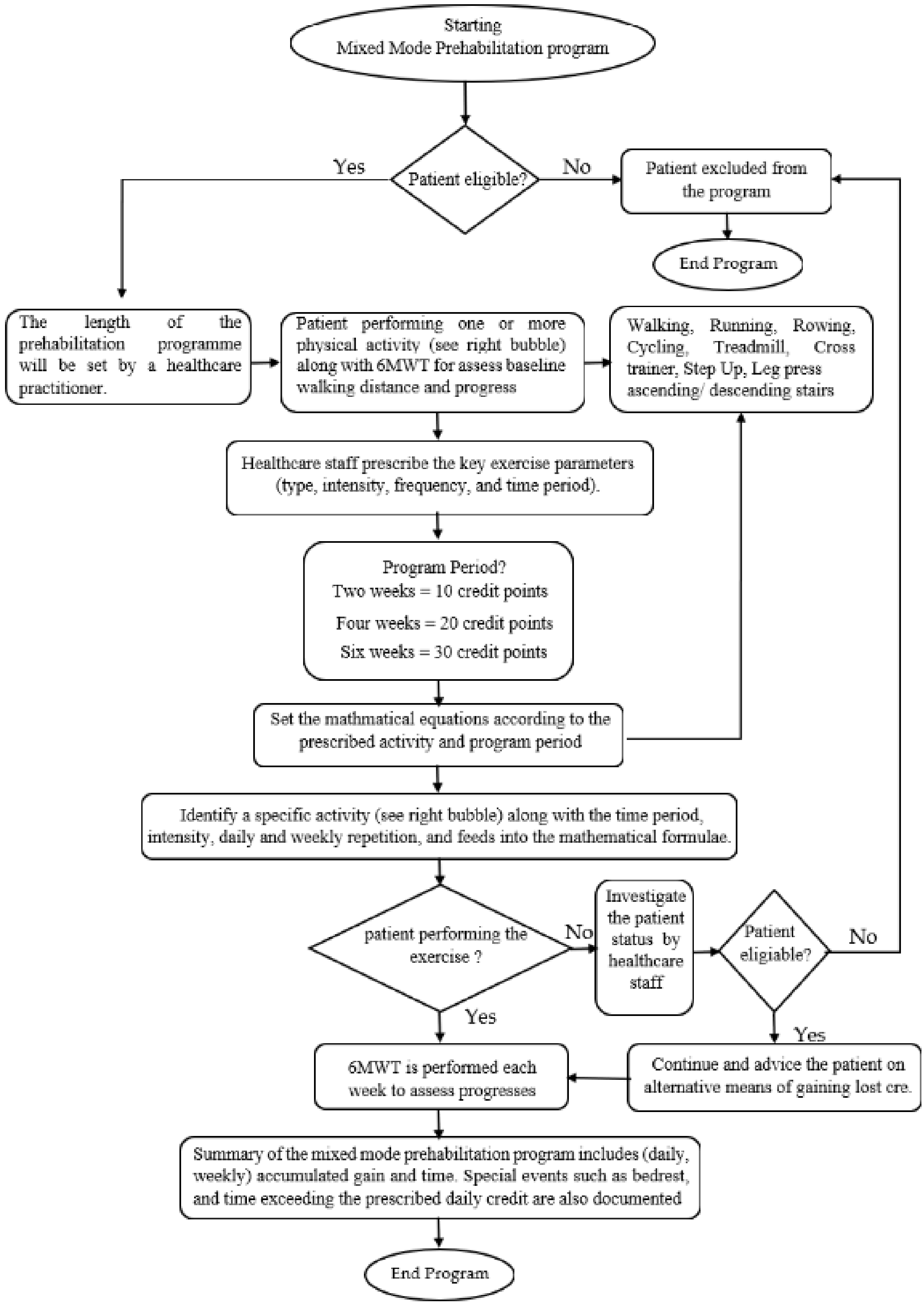


Figure 4.1. The procedure for mixed mode prehabilitation programme.

4.3 Cyber-physical System for Cancer Patient Mixed Mode Prehabilitation

There are three main factors involved in a cyber-physical system that could monitor the prehabilitation program. Namely, the human subject, sensor placement, and IoT System. The human subject involved in the prehabilitation programme could be young, or elderly. They may also be athletic, healthy, or unhealthy. It also includes the environment where the monitoring of the activities occurs such as physiotherapy centre or free-living environment. The sensor placement is the location of the wearable sensor and how it influences the accuracy of identifying the type of activity being performed. Recently, the advancement of wireless microcontroller devices has enabled small and light weight wearable sensors to be easily attached to various location of the human body [97-100, 103, 104, 106, 107, 161]. According to the findings of a previously conducted study [46], the ankle is the best place for sensor location as it produces more consistent and accurate data than other locations. The IoT system provides suitable environment to connect to the wearable sensor via the Internet gateway, to visualise, measure, remotely monitor, and evaluate the outcomes in accordance with the boundaries established when the prehabilitation programme was developed.

4.3.1 IoT system architecture

To construct an IoT system for tracking an integrated mixed mode prehabilitation programme, there are three main components that must be available in this system (Figure 4.2), including:

A. Wearable sensor and movement activity recognition (wearable edge computing)
B. Internet gateway and short-term data analysis (Gateway edge computing)
C. IoT Cloud service and long-term analysis

Figure 4.2 shows the architecture proposed for the IoT-compatible wearable prehabilitation exercise activity monitoring system. Architectural features utilize computational resources in three main levels. These are the wearable wireless sensing level, the IoT gateway (or Internet edge) level, and the cloud level. Each of these steps plays an important role in facilitating the smooth operation of the entire remote monitoring process of the patient's prehabilitation.

The proposed wearable wireless activity tracker includes sensor modules that are responsible for detecting human movement in real time. Here, the tracker provides four main functionalities, namely, sensor data acquisition (including sensor selection, sample rate, and acquisition duration); data storage (short-term data storage for motion detection purposes and long-term backup data storage); data processing (including data calibration and FFT signal processing); and data communication (to regulate message and data communication patterns). Embedded computing played an important role in WSD such as (FFT techniques) that is reducing the amount of transmitting data to the upper level and reduction the of communication overheads. The above points have been considered in the conceptual design of the WSD.

Gateways (e.g., Raspberry Pi, laptop, or smart mobile devices) can process one or more wearable sensors that are involved in one or more types of detection. These can be multiple wireless portable devices used by one user, or multiple users. The gateway has four main functions:

1. Data communication with both WSD on one side and the Internet on the other. In this context the gateway acts as protocol converter from the WSD protocol to the Internet connectivity related protocol and vice versa.
2. Multi stages of the activity recognitions and prehabilitation efforts calculations.
3. Data storage for short- and medium-term repository of movement and processed data. Data can be managed with Mongo DB and MySQL databases

At the cloud level, the platform should use both user interactions and higher-level data analytics throughout the pre-approval process. In addition, long-term process data and event monitoring takes place in real time during the entire prehabilitation cycle. Key functions occurring at the cloud level include an HTTP protocol for gateway device communication for transferring data from a gateway to the cloud, a cloud data repository that consists of a health and knowledge data repository. On the other side, the long-term data analysis, deep learning, alert messaging, and big data managements all are considered in the conceptual design during selection the cloud services. The support of the data available in the cloud repository is intended for long-term storage and further analysis. In addition, the classification of movement activities, the detection of prehabilitation progress model events and the creation of various screens for data visualization also take place at the cloud level.

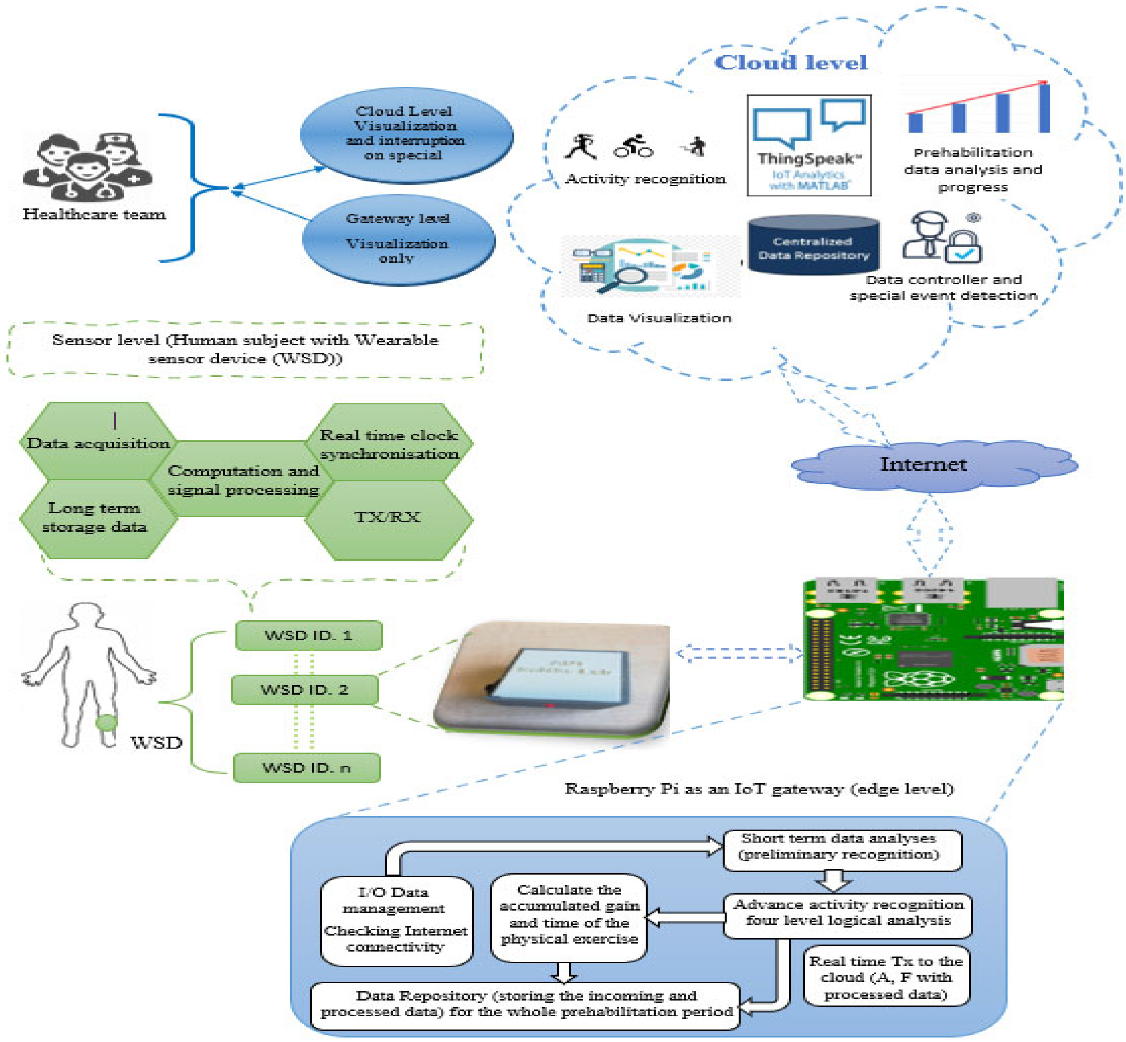


Figure 4.2. IoT architecture for cyber-physical system of mixed mode prehabilitation programme.

A. Wearable sensor and movement activity recognition

A number of researchers have used the data collected from accelerometer sensor(s) placed on the human subjects to recognise and classify human physical activities [97-100, 103, 104, 106, 107, 161]. Sensor units typically incorporate accelerometery technology to evaluate movement magnitude and provide an estimation of metabolic demands of physical activities. Specific movement tasks may be better detected using inertial measurement units (IMUs), which incorporate accelerometers, gyroscopes, and magnetometers, allowing for the use of multiple sensor outputs to identify specific movement tasks. Accelerometers measure the rate of change of velocity via linear accelerations, and gyroscopes measure orientation and angular velocity. Magnetometers provide directional information, similar to a compass, by measuring the magnetic field strength [122]. In this study, a single 3D accelerometer has been used for recognising nine physical activities as described in our previous publications [46, 47]. A 3D accelerometer cannot be used as a wearable sensor device (WSD) without the assistance of another device for this study;

as discussed in Chapter 3, the Microduino was selected as the wearable sensor owing to its compact size, availability of data sources, functionality, and capability to interact with open-source software. The proposed WSD undergoes a number of edge computing processes. First, the microcontroller sends an order to the SD board to create a file that stores the data in an SD card. Next, the microcontroller initialises the variable iteration and sets the 16-bit timer to zero. This information is then sent to the 3D accelerometer for calibration and orientation for the first 4 seconds of data collection. At the same time, the microcontroller requests the date and time information from the real-time clock (RTC) model and enables the timer interrupt by setting the Timer Interrupt Mask (TIMSK) register to start the equally spaced increment of the iteration variable.

Following this procedure, the system starts creating a timestamp for the current reading. The time is accurately calculated by the iteration variable, which is incremented by the timer interrupt.

The system then checks for the occurrence of a new interrupt. As soon as the interrupt occurs, the variable is incremented by 1, making it different from its previous value. This triggers the 3D accelerometer to request accelerometer data stored in the temporary variables (tempx, tempy, tempz) because the buffer used to store the data is simultaneously storing the data from the previous four seconds. Four-second epochs of data were chosen because this is the minimum period required to recognise the activity without any distortion [46, 47].

The gathered four seconds (512 samples) of raw 3D accelerometer X, Y, and Z data are averaged separately and then subtracted from the original axis value to obtain a 512 DC offset value. One filtered sample for each fourth reading is then selected. The result is 128-filtered DC offset data for (XYZ reading). At this stage, a fast Fourier transform (FFT) is applied to the 128 DC offset data to extract the dominant amplitude and frequency of 128 samples within each four-second epoch.

Once the string containing acceleration values and FFT amplitude and frequency measures of the last four seconds is prepared, the data from temporary variables are copied to the main buffer. At this stage, a complete string is prepared containing the timestamp, count, ID, raw X, Y, and Z acceleration data, and FFT results. This information is then stored on a long term storage (SD card) 16 GB, which can hold data for about 10 days if used continuously for 24 hours a day [48]. This will be repeated until the end of each four seconds, and then the payload containing necessary information, such as node ID, packet number, timestamp, and FFT results (amplitude and frequency of the dominant spectrum), is prepared to send to the gateway [48]. A communication protocol is then used for establishing connection between the WSD and the gateway node.

B. Internet gateway and short-term data analysis

We selected the Raspberry Pi as a gateway in this study because it is a single-board computer (SBC), which means it runs in a full operating system and has enough peripherals (memory, CPU, and power regulation) to begin execution without further hardware. The Raspberry Pi can run various operating systems and only needs power to start-up [162]. Using the onboard general-purpose input/output (GPIO) connections, these boards may be interfaced with sensors and actuators. In addition, the Raspberry Pi has the ability to establish a Wi-Fi connection either onboard or via the Ethernet cable.

For transmitting data and communication between the WSD and the gateway it is strongly suggested that both devices use the same transceiver model to ensure compatibility in terms of specs and capabilities. The transceiver must be capable of bidirectional data transmission at an acceptable bitrate and at a reasonable range in order to ensure the security of the link between the WSD and the gateway in both outdoor and indoor environments. A free licence frequency band, multichannel with sufficient bandwidth, will allow the gateway to handle multiple WSDs at the same time. An additional specification has to be present that the hub receiver can switch from listening to transmitting at any time to avoid data loss [43]. In the case of multiple senders attempting to send the data at the same time, at least one of the senders' data is received if the packets overlap, and the other senders are promoted to send the data again. Senders require acknowledgement from the receiver for a successful transmission of data, else they assume that the network is not available and try sending the data again. Therefore, all the data are transmitted sequentially, and nothing is lost. Thus, the received data of amplitude (A) and frequency (F) act as preliminary activity recognition information and are compared with the preliminary stored database [46].

The flowchart depicted in Figure 4.3 shows the enrolment of the Raspberry Pi as an edge computing, short-term data processing and medium-term repository data.

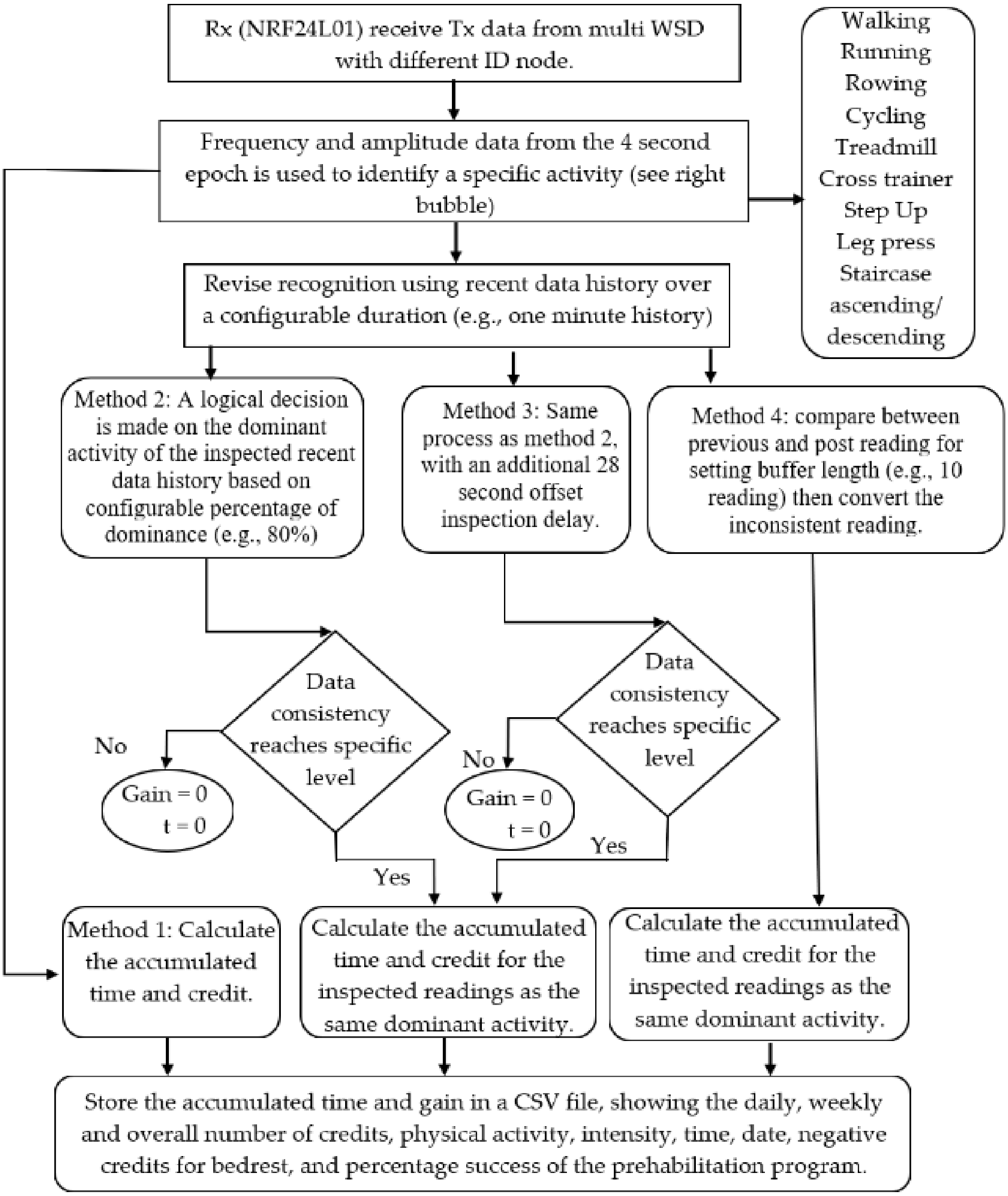


Figure 4.3. Raspberry Pi as an IoT gateway edge processing node.

Each type of activity is presented with 'crisp' values of frequency and intensity. Practically, these crisp values represent the centre of gravity for a particular activity. There is a 'fuzzy span' around the centre values for each movement. Different movements have a certain extent of overlap among each other. This overlap leads to some activities not being recognised accurately, which, in turn, may result in the loss of some credited efforts. A number of studies recruit machine learning and deep learning approaches to overcome this issue [163, 164]. However, in this study, special logical approaches have been explored to enhance the activity recognition and credited physical effort calculations. In an attempt to reduce the impact of overlaps of power spectrum frequency and amplitude measures among the recognised activities, the extracted recognised activities have to be examined using four simple logical methods based on short-term history data.

The first recognition method is a direct method and is based on the direct preliminary activity recognition, which must be stored in the separate table as an initial database. Every four seconds of incoming data (frequency and amplitude measures) are compared with a relational table comprising activity codes representing average frequency and intensity values for each exercise.

The second and third recognition methods are fairly similar. Both are based on estimating recognition consistency by examining a short-term history of the data recognised using the first method. Each minute of incoming data (15 readings of four seconds of recognised outcomes) are stored in a temporal buffer and then recognised by calculating the majority of occurrences of specific activities detected via the first method. If the consistency of a particular activity is more than a certain percentage of the total activity (e.g., more than 80% of data represents the amplitude and frequency components of a specific activity), then all the data throughout that minute are credited as the dominant single activity. If this consistency is not achieved, the system shows nonspecific activity (NSA). The third method is similar to the second with the additional moving one-minute window that overlaps by 28 seconds (a total of seven, four-second epochs). This improves the recognition timing precision by covering the transition time between activities. The fourth method keeps tract of the type of recognized physical movement over predefined span of time. When the time expire, it checks on the consistence of the recognition through identifying the movement that majority score and remove the outliers. For example, if the instances of the recognized movements over 20 seconds (which is equivalent to 5 recognized instances) are CL,CL,CL,WM,CL then the method correct the WM and replace it with CL. This method use separate buffer and retain the original data record for future analysis. The length of both buffers is 5 readings which is 20 sec. Buffer size has a flexibility to increase or reduce. The number of previous readings to compare with ranges from one to (n/2), where n is the buffer length. Next, the output results of all the four methods must be stored in a comma-separated value (CSV) file for further analysis. The system has to store the full summary of incoming and processed data for the full prehabilitation period of each patient. In addition, researchers, designers, and healthcare staff can access the gateway for a summary with the different level of interventions. The researcher and designer have the authority to interrupt the different stages of data processing for system development, research, and troubleshooting. Furthermore, healthcare staff (physiotherapist and doctor) are authorised to access data visualisation, programme summary, prehabilitation progress, and creating a reaction in such emergency events by phone call or message when there is no physical exercise or movement action for a certain time period.

C. Internet Cloud-Level Functionality

Cloud computing works by allowing client devices to access data from the Internet, remote servers, databases, and computers. Internet network connection front-end includes client devices, browsers, networks, and cloud software applications. For data acquisition, frames from the gateway or edge device, communication protocols, such as HTTP and MQTT, can be utilised. The cloud has its own data repository that may be utilised to store and manage patient activity movement data, as well as any other associated knowledge data. Data computation techniques, such as digital signal processing, artificial intelligence, and machine learning approaches can be used with the data available in the cloud repository. Furthermore, cloud resources play a prime role in data visualisation, activity event detection, and emergency response. TS and IBM Analytics are two examples of commercially available tools. A reaction can be triggered via a number of services, such as sending a text message or email or buzzing an emergency alert so that immediate action can be taken [48].

TS, a cloud platform that collects data in real time and saves the same, was employed in this study. It enables the application to construct IoT-based processing and visualisation. MATLAB, a computational tool, was included in the platform and used for any possible data calculation or learning process. As computing resources are pertinent to most of the operational requirements of the process, using such a tool could help make greater and precise sense of the acquired data.

TS's core functionality is based on its communication channels, which can include up to eight fields of various data types, three location fields, and one channel field for status value. It updates the data every second and can handle approximately 90,000 messages per day, overcoming the lag in the transmission of processed data from the gateway to the cloud [165].

4.4 Summary

The key elements and boundaries of both supervised and unsupervised programmes have been extracted to structure a new prehabilitation model, which is called a "mixed mode prehabilitation model." The new model incorporates elements of previous programs, such as confirming the performance of physical exercise as prescribed in both supervised and unsupervised settings. Factors like bedrest period, threshold time, and intensity level have been included in this model. On the other hand, mathematical formulas have been created to express the mixed mode prehabilitation program in terms of numerical ways. The formulas show the efforts, intensities, time, and physical type by accumulating credit gain per single or multi sessions. On top of that, the drawback of the supervised and unsupervised programmes has been eliminated. For example, in a supervised program, multiple visits to the hospital or physiotherapist centre, while in an unsupervised program, there is uncertainty about performing prescribed physical activity. To cover the above features, the cyber-physical system to support the mixed mode prehabilitation program was designed for that reason. The three tiers of the cyber physical system (WSD, gateway, and cloud) were used as the basis for this system's design. When it comes to gathering and delivering the patient data to the upper level of the system, WSD is in charge of this. However, the gateway function is responsible for receiving and storing the received multi WSD data, securing connection between the WSD and cloud as well as processing it. On the third level of the cloud, data will be visualised, stored for the long term, and processed further.

Chapter 5 Concept Modelling and Implementation

5.0 Introduction

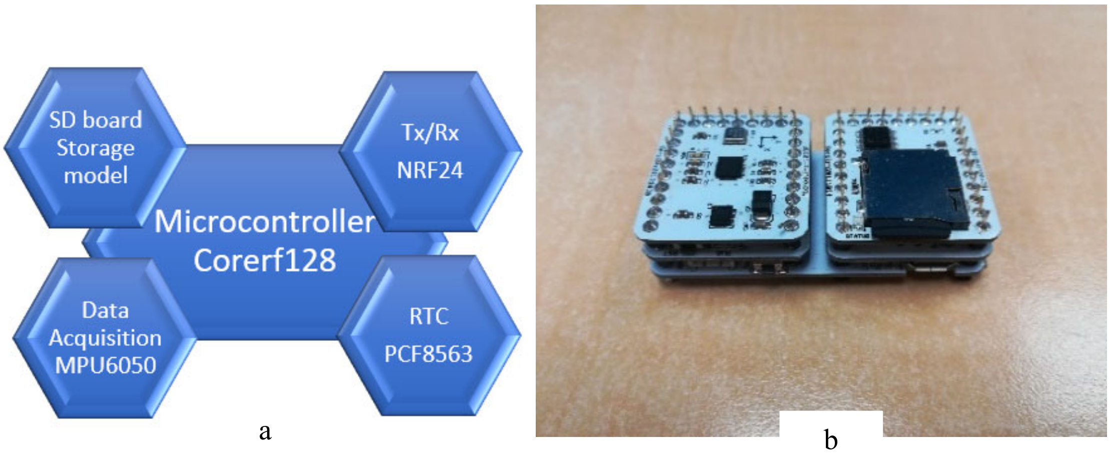
This chapter discusses the design and implementation of a monitoring system for supporting the tracking of movement activities in mixed mode prehabilitation programmes. The development and testing of the model and host environment are discussed here. Section 5.1 discusses the different components of the movement monitoring system that supports the mixed mode prehabilitation program. The design and implementation of WSD with its critical issues and the data flow processes implementation are discussed in section 5.2. Sections 5.3 and 5.4 examine the function of edge computing and data processing embedded within the IoT-gateway. Section 5.5 examines the software functionalities at the cloud level. Section 5.6 details the methods involved in implementing a mixed mode prehabilitation programme recruiting data from previously discussed prehabilitation models (supervised and unsupervised). Section 5.7 offer summarises to chapter 5 outcomes and challenges.

5.1 Movement Monitoring System Implementation and Testing

The monitoring system that supports the mixed-mode prehabilitation model has been highlighted in detail in sections 4.3–4.6. The main three operational components involved are the wireless sensing device (WSD), the Internet gateway device, and the resources established at the TS cloud services. This section discusses the design, implementation, and testing of these components, and provides a reflection on the overall system performance.

5.1.1 Wearable Sensor Device (WSD) Development and Implementation.

The WSD is the front-end component of the IoT cyber-physical system and is responsible for sensing the movement and capturing the related raw data from the user. The WSD size, power consumption, computation functionality requirements, data storage, and communication requirements are all examined in this design. As explained in Section 4.3 and Figure 4.3, the architecture of the WSD for human physical activity consists of five main functionalities (see Figures 5.1a and 5.1b), namely movement sensing, timestamped data acquisition and calibration, data compression and feature recognition, data storage, and data communication.



a b

Figure 5.1 a. Microduino model, **b.** stackable style.

In this study, Microduino modules were utilised for assembling the WSD. In addition to its small size and stackable hardware board design, the Microduino has different functionality that can fulfil the WSD requirements. For movement sensing and data acquisition, the MPU6050 (3D accelerometer) is used. The 3D accelerometer has four different ranges of acceleration with different sensitivity ranges. The (±2 g) was selected for two reasons. First, it offers good sensitivity. The second reason is due to the type of activities performed in by elderlies which, in particular during pre-surgery prehabilitation programmes, do not involve high acceleration [1]. The Microduino corerf128 is used as the core microcontroller for the WSD, which is responsible for managing, processing, storing, and communicating the data between the controller and other WSD modules.

For data storage, the SD board was added to the sensor node. Within a wearable device, the SD card is utilised for long-term storage. This can be used to store continuous raw accelerometer data activity events over the long term (around 70 MB per hour). Accordingly, the 16 GB SD card covers 210 hours of continuous data storage, which can cover the whole prehabilitation programme period. The RTC PCF8563 and the Nordic NRF24 chipsets were added to the WSD to create a data timestamp, and for transmitting and receiving data.

All the above boards were assembled into a single container to formulate the WSD. A rechargeable 3.7 V battery is used as DC power supply. The battery size and capacity are selected carefully to allow the WSD unit to work for around 20 hours with comfort to cover the daytime activity. The container of the WSD is designed and manufactured using a 3D printer (Figure 5.2a and 5.2b). A fabric strip is used to hold the WSD unit. The level of patient comfort is taken into consideration while designing the fabric strip and 3D box. The device can be attached to the patient's ankle while performing the physical activity (Figure 5.2c).

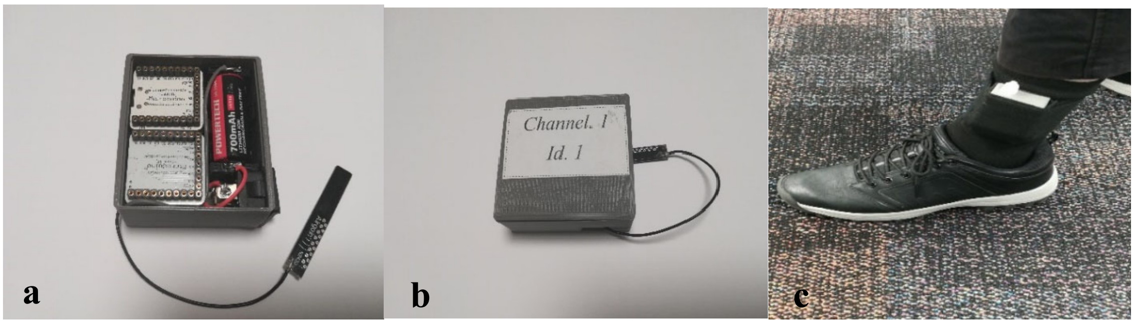


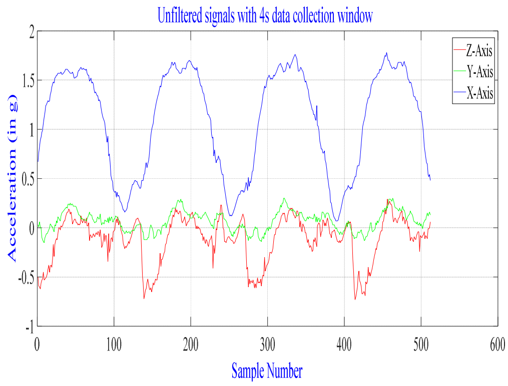
Figure 5.2 a, and **b.** Microduino stack with a battery component of the WSD, **c.** Fabric strap to fixate the WSD to the ankle of the participant.

As discussed in Sections 4.3.1 and 4.3.2, once the sensor is powered on, the microcontroller sends a request to the SD board to create a file for the data storage, at the same time initialising the variable and requesting the date and time from the RTC. This enables the timer to interrupt by setting the microcontroller register to generate the equally spaced increment of the iteration variable. The real-time 3D accelerometer data are collected at a sampling frequency of 128 Hz for each activity. This sampling frequency is considerably higher than the highest spectral frequency of 20 Hz documented during everyday activities [97, 103, 114] and accounts for any fast state changes during the prehabilitation exercises [76, 166]. Accordingly, the loop starts to collect 128 samples, equally spaced at four-second intervals giving a total 512 samples of raw XYZ acceleration data every four seconds. The illustration of Algorithm 5.1 shows the SD card initialisation, and the process of storing the consecutive 4 seconds of data in a temporary buffer. As illustrated in Section 2.4, the accelerometer sensor data could be analysed either in time or frequency domain. Time domain analysis is relatively fast and requires less memory than frequency analysis. Frequency analysis uses relatively demanding processing techniques such as FFT. However, frequency domain systems are relatively inexpensive, easy to develop, and can provide a very fast temporal sampling. It also helps compressing the acquired data significantly at the WSD level. Accordingly, the FFT technique was used to process readings of the raw 3D accelerometer data.

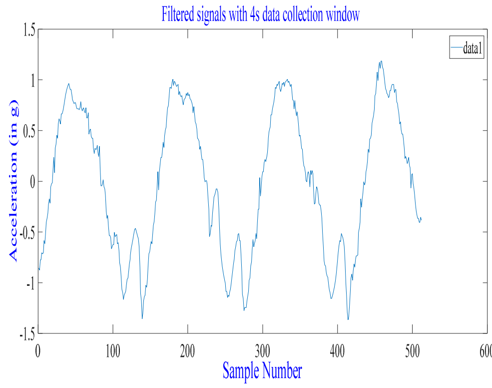
```
new_File = Init(SD_Card_module).
set_timer_16bit(0).
init(itr).
date = Get_RTC_date(); //get Real time clock date
time = Get_RTC_time(); // get Real time clock time
enable_timer_interrupt(TIMSK5); // enable timer
while() // Loop starts to collect the 128 samples per sec, equally spaced in the 4sec interval.
{
dat = get_data_reg(MPU6050); // Ask for the data from MPU6050 module
}
timestamp = timestamp(Date,Time); // generate timestamp
//Initialise buffer for x,y and z axis acceleration
tempax = init(Xaxis);
tempay = init(Yaxis);
tempaz = init(Zaxis);

Xsensitivity = Xaxis/16384;
Ysensitivity = Yaxis/16384;
Zsensitivity = Zaxis/16384;

acc = tempax + tempay + tempaz;
vReal[itr-1] = acc
vImag[itr-1] = 0.0
sumx += tempax; (Variable to store the sum of acceleration of x axis for 512 samples)
sumy += tempay; (Variable to store the sum of acceleration of y axis for 512 samples)
sumz += tempaz; (Variable to store the sum of acceleration of z axis for 512 samples)

for (itr=1; itr<512;itr++) //Creating loop of 1 to 512 reading
{
 Xaxis [itr] = tempax; (Storing the temporary value of X-axis in the 512 array)
 Yaxis [itr] = tempay; (Storing the temporary value of Y-axis in the 512 array)
 Zaxis [itr] = tempaz; (Storing the temporary value of Z-axis in the 512 array)
}
```

Algorithm 5.1. The pseudo-code and the steps used in the WSD algorithm.

Unlike other types of sensors, accelerometer sensors can be influenced by three key factors: calibration; location; and orientation. Because of differences in calibration, location, orientation, or combination of these, two accelerometer sensors can produce different results with the same movement action [167]. To avoid these problems a mean value of the 512 samples of the raw X, Y and Z acceleration data over each 4 second period was then calculated (Figure 3a), removing the DC offset, (Figure 3b) and taking the average of every four samples. This would down-size the sampling rate to 32 Hz to comply with the 20 Hz suggested for everyday activities. The result of this process was 128-DC offset filtered data. Algorithm 5.2 explains the steps of filtering data, DC offset, and preparing data for the FFT technique.



(a)



(b)

Figure5.3 a. Raw signal after applying filtering technique, **b.** Raw signal before applying filtering technique.

Raw X-axis, Y-axis and Z-axis accelerometer data gathered from the accelerometer and stored in temporary variables (tempx, tempy, tempz).

While() //Loop starts to collect the 128 samples, equally spaced in the 4sec interval.

{

dat = get_data_reg (MPU6050); // Ask for the data from MPU6050 module

}

//Average values taken for 512 values of X-axis, Y-axis, and Z-axis accelerometer data.

avgx = sumx / 512;

avgy = sumy / 512;

avgz = sumz / 512;

Average value of X, Y, and Z is subtracted from the whole 512 X-axis, Y-axis, and Z-axis accelerometer data as follows:

Loop I =1 to 512

X-axis -Mean X

Y-axis -Mean Y

Z-axis -Mean Z

Close loop

Select each 4th reading and store it in a separated buffer for 128 DC offset of XYZ-data.

Algorithm 5.2. Pseudo-code for implementation of de-orientation, DC offset of X-, Y-, and Z-axis accelerometer data.

Next, the FFT techniques were applied to the 128 samples of the DC offset data to extract the maximum amplitude and corresponding frequency after every four seconds. Figure 5.4 summarises how each four-second time window of raw X, Y and Z data where compressed and processed. As per the real-time data analysis, four-second duration was regarded as the minimum time window for detecting an activity without signal distortion or loss of information. Figure 5.5a shows how the amplitude features of the signal are influenced by the window of sampling time. There is no clear difference in amplitude measured for data analysed over a period of four seconds (Figure 5.5b) and 10 seconds (Figure 5.5c). However, when the sample period is limited to three seconds (Figure 5.5d), there is a decrease in amplitude compared to both four and 10 seconds (Figure 5.5). In accordance with these findings, the collected test data were analysed using successive four-second windows of time.

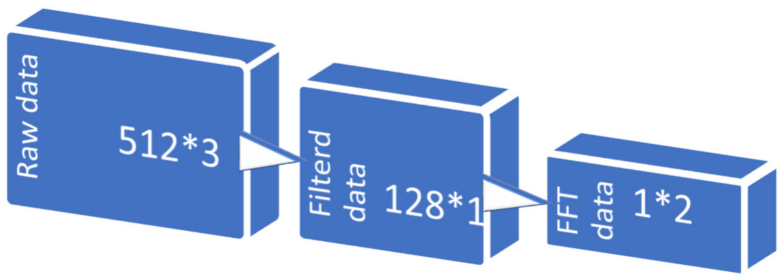


Figure 5.4. Showing the compression and processing of 3D X,Y and Z acceleration data over a 4 second time window.

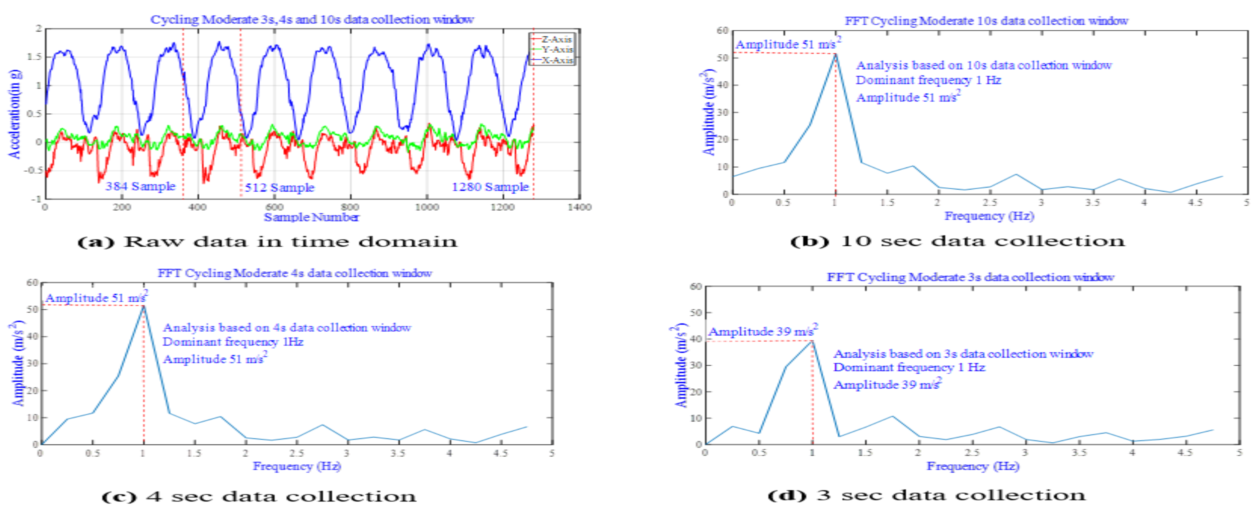


Figure 5.5. The outcomes of the FFT technique used to identify the dominant frequency and the associated acceleration from 10, four, and three-second data collection windows.

Amplitude and frequency, along with node ID, count number, date, time, and raw X, Y and Z data were stored in the SD card as long-term backup data. The extracted amplitude and frequency, along with the desired data, were sent to the gateway every four seconds. Figure 5.6 shows the data storage pattern in the SD card, while Figure 5.7 shows the summary of the WSD data processing.

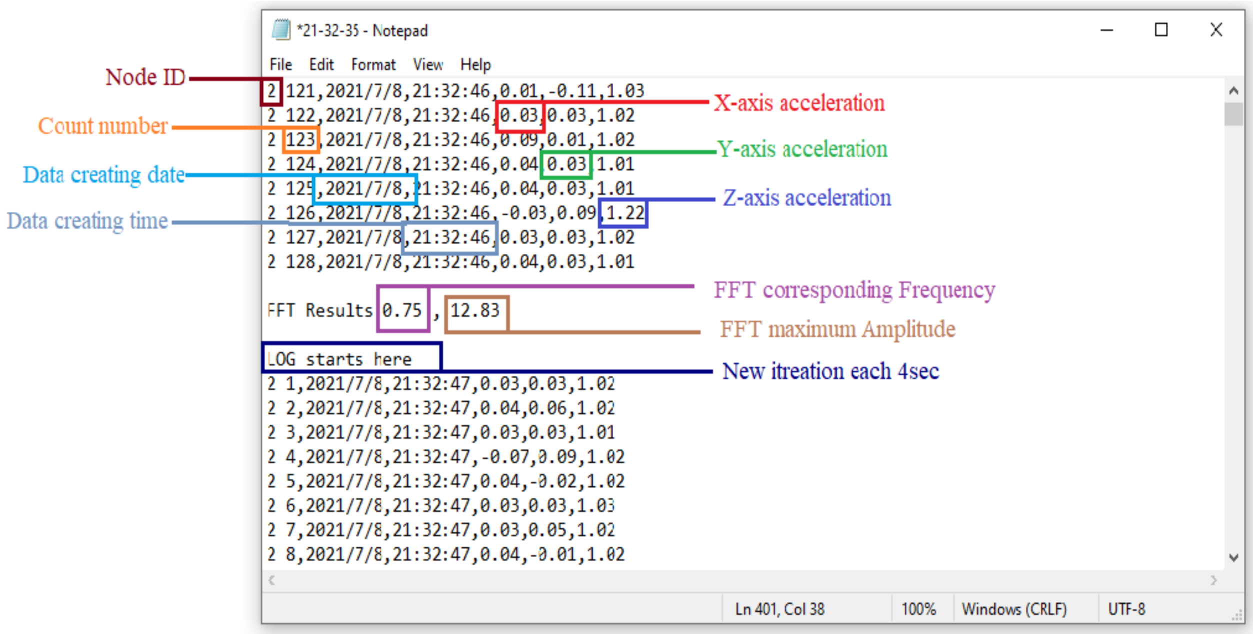


Figure 5.6. The pattern of real-time storing of X, Y, and Z raw and processed FFT data.

Figure 5.7 presents a brief description of the WSD dataflow and shows the data processing from an early stage of gathering data from the accelerometer until the transmitting of processed data to the gateway. The microcontroller is the core of the system. Once the sensor is turned on, the microcontroller starts managing and controlling the orders on the different board functions to ensure that the data process follows smoothly without interruptions. The microcontroller requests the SD board to create a file for storing raw and processed data, while the raw data are stored in the temporal file for calibration and further processing. The RTC is requested to add a timestamp to the stored data; then, after completion of data processing, the full string of data can be stored on the SD card while the payload is prepared for the data transmission to the gateway. This process is repeated until the WSD is switched off.

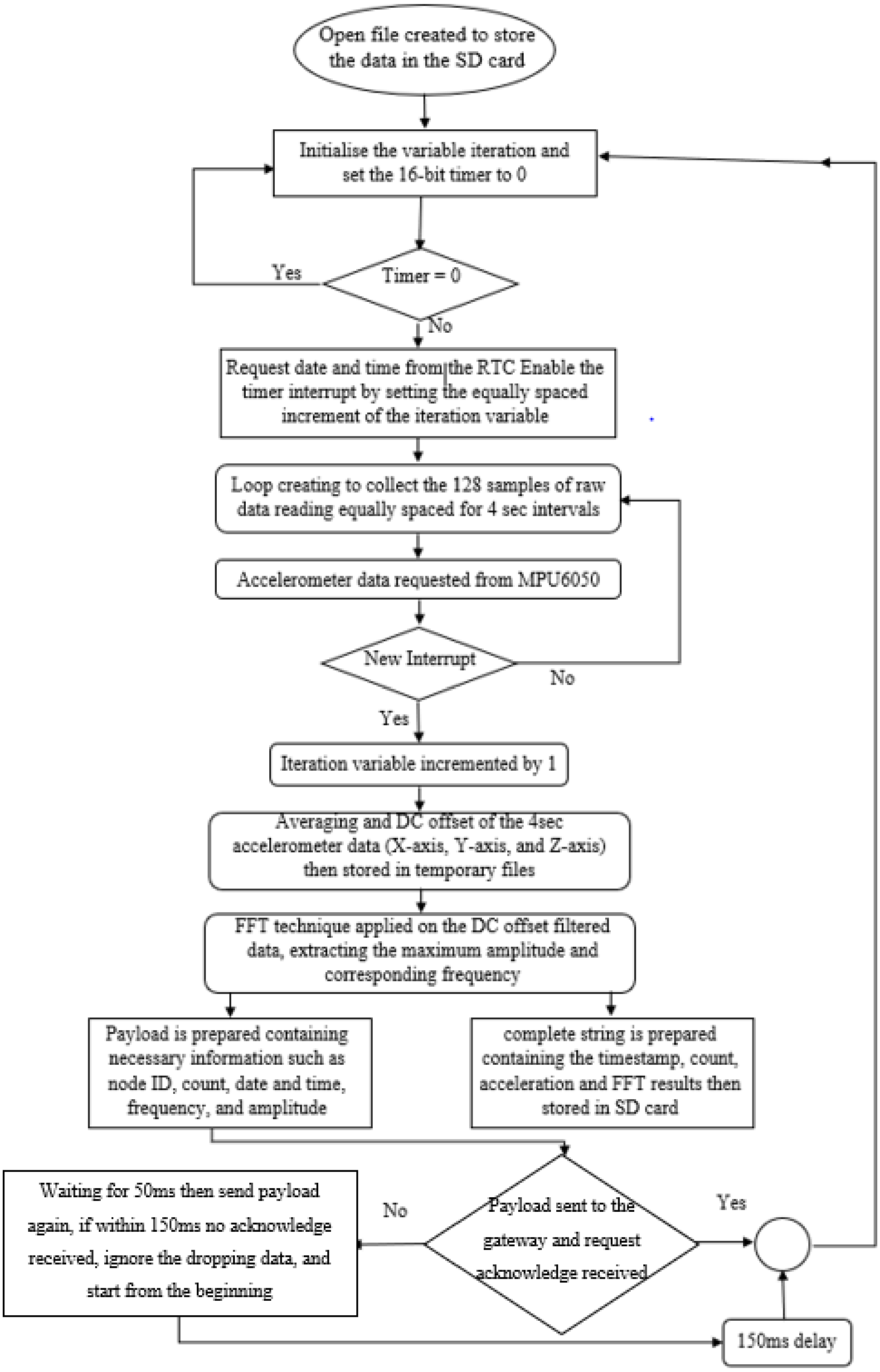


Figure 5.7. WSD data flow and process.

5. 2 WSD Critical Design Issues

As discussed in Sections 4.3 and 5.1, the design and implementation of WSD takes a number of factors into consideration. The WSD should be attached to the patient's ankle and therefore, a small size and light weight are the key factors that need to be considered. In this study, the Microduino stack (sensors, microcontroller, and other supporting boards) were used to offer the flexibility for testing the various combinations of hardware and software functional components. We also investigated the effects of different operational modes on the energy consumption of the wearable device. As discussed in Section 3.2, the Microduino hardware can run on a 3.3V battery so the wearable nodes are powered by a ½ AA rechargeable battery of 700 mAh at 3.7V. With the possible reduction in computation and communication power, the battery can function continuously for 20 hours full operational mode allowing it to be recharged during the user's bedtime.

An additional critical issue discussed and addressed throughout the WSD design is whether raw or processed data must be stored in the SD card or sent to the upper level (gateway). As previously discussed in Section 5.2.1 the best-case scenario of data storage is that the raw and fully FFT processed data should be stored in the SD card every four seconds. This was chosen for two reasons. Firstly, the time spent on data storage of both processed and raw data is only slightly more than the raw data with no significant effect on the process. Secondly, storing raw data provides a long-term back up for both researcher and healthcare staff to use for further analysis.

Different scenarios were examined to optimise the four-second data transmission of raw and processed data to the gateway, as shown in Table 5.1 and Figure 5.4. Table 5.2 shows the comparison between the different scenarios of data transmission. The measurements of the drop percentage rate have been taken when the gateway is serving as a single node only. Sending 512 samples per second of raw or 128 samples of filtered data generates high traffic on the receiver side, especially when multiple sensors are transmitting data at the same time. Additionally, the gateway will be fully occupied to process 512 raw data with the filtered and applied FFT technique to determine frequency and amplitude every four seconds. A combination of these factors led to increase in the percentage of data dropping (7% for 512 samples and 1.2% for 128 samples per second) and an overall reduction in system performance (Table 5.2). Thus, the best-case scenario is sending fully processed data (FFT amplitude (A) and frequency (F) data) every four seconds, which resulted in minimal or no loss of data. Another advantage of transmitting the processed amplitude and frequency data every four seconds is that of using the lower minimal data transmission rate of 250 kbps. This lower transmission rate enabled an increase in the transmitting range and reduced the traffic at the front-end receiver. This also enhanced the overall Tx/Rx performance by offering spare time for the Tx in case there is no acknowledgement received from the Rx. In addition, computation time on the gateway side is reduced. Accordingly, transmission of processed amplitude and frequency data from 4 seconds of 3-D accelerometer data improved the gateway's operating performance and increased the number of serving nodes that could be used (Table 5.2).

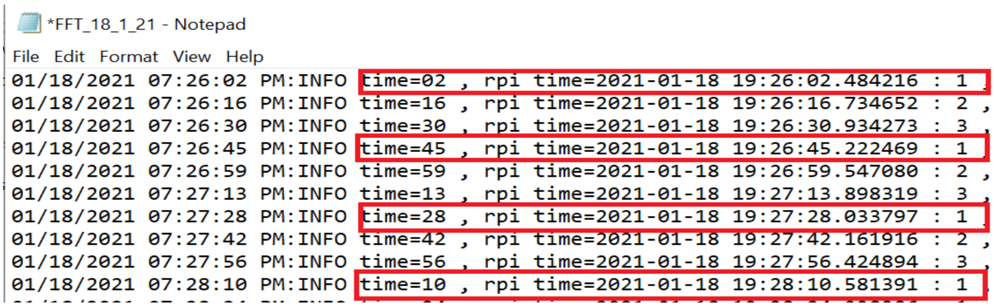

```
*FFT_18_1_21 - Notepad
File  Edit  Format  View  Help
01/18/2021 07:26:02 PM:INFO time=02 , rpi time=2021-01-18 19:26:02.484216 : 1 ,
01/18/2021 07:26:16 PM:INFO time=16 , rpi time=2021-01-18 19:26:16.734652 : 2 ,
01/18/2021 07:26:30 PM:INFO time=30 , rpi time=2021-01-18 19:26:30.934273 : 3 ,
01/18/2021 07:26:45 PM:INFO time=45 , rpi time=2021-01-18 19:26:45.222469 : 1 ,
01/18/2021 07:26:59 PM:INFO time=59 , rpi time=2021-01-18 19:26:59.547080 : 2 ,
01/18/2021 07:27:13 PM:INFO time=13 , rpi time=2021-01-18 19:27:13.898319 : 3 ,
01/18/2021 07:27:28 PM:INFO time=28 , rpi time=2021-01-18 19:27:28.033797 : 1 ,
01/18/2021 07:27:42 PM:INFO time=42 , rpi time=2021-01-18 19:27:42.161916 : 2 ,
01/18/2021 07:27:56 PM:INFO time=56 , rpi time=2021-01-18 19:27:56.424894 : 3 ,
01/18/2021 07:28:10 PM:INFO time=10 , rpi time=2021-01-18 19:28:10.581391 : 1 ,
```

Figure 5.8. Multiuser four-second data packets drop when sending 512 raw data to the gateway.

The collection window and the time gap between transmissions are improved to attain better performance. As discussed in Sections 4.3 and 5.1.3, four-second duration is the minimum data-collection window without any distortions. However, any extra time during the data collection process will reduce the power consumption and will not affect the signal quality. The extended time on the data-collection window led to missing some data during the collection process. Furthermore, an increase in the time gap between each data transmission to the upper level (gateway) will reduce data traffic and increase the number of serving nodes, but the latency of activity recognition will be longer, and the performance of the system for the activity recognition will reduce accordingly.

Table 5.1. The node and gateway performance with different scenarios.

Bulk of transmitted data	% Of packet loss at gateway (5 minutes)	Gateway performance (max node without latency)	battery running live	Node power consumption (mW)	TX range	Data rate
512 Raw	7%	2	16.30 h	157	¾ of 250 kbps	1Mbps
128 Filtered	1.2%	3	17.2 h	150	1	250 Kbps
FFT (A&F)	0.02%	6	20 h	134	1	250 Kbps

5.3 IoT Gateway Edge Computing

As discussed earlier, the main reason behind selecting the Raspberry Pi as an IoT gateway is that it is a single board computer with a full operating system (Figures 5.9a and 5.9b). As explained in the previous section, the final stage of WSD data processing involves transmitting the payload along with the extracted FFT data to the gateway. The NRF24 transceiver is placed on WSD and the gateway as well.

Similar to the WSD, the Raspberry Pi must be small and portable to allow the patient to carry it in his/her bag or pocket. This will help continuity for local monitoring and opportunistic connectivity for global monitoring. Figure 5.9 a and b show the RPi3B role as a base station (gateway) indicating the dimensions with the container (8.5 *6*2.5 cm) while the total weight with portable rechargeable battery is 145g. The WSD prototype dimensions and weight are (6*4.5*2.5 cm) and 76g (Figure 5.9 c). The light weight and reasonably small size of the gateway (Raspberry Pi) and WSD offers the comfortable use for the participants. Furthermore, opensource smartphone applications related to the cloud visualization such as TS provide an easy way for the real-time visualization of data gathered and processed on both WSD and gateway. These features make the WSD more attractive to the patient and clinician for monitoring different kinds of activity.

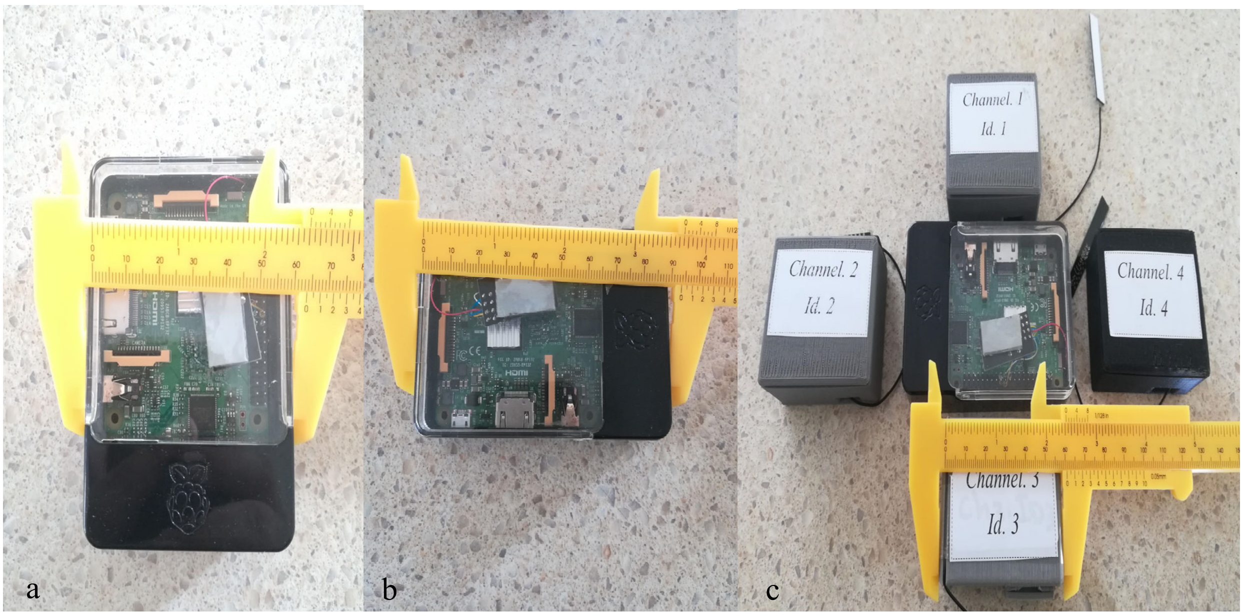


Figure 5.9. a and **b** RPi3B as a base station, **c.** RPi3B with multi WSD.

5.3.1 Preliminarily physical activity recognition.

As per the initial physical activities performed by the patient in the hospital or physiotherapist centre, the system stored and analysed the WSD data to create a preliminarily data of each physical activity, as shown in Table 5.2.

Table 5.2. Results of frequency analysis of 3D accelerometer data for nine different types of activity at three different intensities collected from a sensor placed on the ankle of five participants [46].

No.	Mode of Exercise	Intensity	Frequency (Hz)	Amplitude (m/s2)	Estimated Indicator for Measure of Intensity
1	Walking (W)	L	1.5	15–32	4 km/h
		M	2	38–60	5 km/h
		V	2.25–2.5	45–75	6 km/h
2	Running (RU)	L	3	55–70	8 km/h
		M	3.25	55–75	10 km/h
		V	NA	NA	NA
3	Treadmill (TM)	L	1.75	20–25	4.5 km/h
		M	2	45–55	5.5 km/h
		V	2.25	50–60	6.5 km/h
4	Cycling (C)	L	0.75–1	20–30	50 rpm
		M	1–1.25	30–55	70 rpm
		V	1.25–1.5	40–80	90 rpm
5	Cross-trainer (CT)	L	0.75-1	8–18	50 rpm
		M	1–1.25	20–28	70 rpm
		V	1.5	30–60	90 rpm
6	Rowing (RO)	L	0.25	4–6	50 Watt
		M	0.5	11–15	70 Watt
		V	0.75	18–26	100 Watt
7	Staircase ascension STRM	L	0.75 and 1.25	30–35 and 15–25	No consistency in both F and A
	Staircase descension	L	0.75 and 1.5	20–30 and 15–25	
8	Step Ups (STP)	L	1.5	14–18	15 cm height
		M	1.5	20–25	20 cm height
		V	1.75	22–26	30 cm height

		L	0.25	5–6	90 kg, 20 times each session
9	Leg Press (LEP)	M	1–2	3–5	96 kg, 20 times each session
		V	0.5–3.75	0.5–5	115 kg, 20 times each session

The nine typical physical activities were further subdivided into 27 different identification groups based on the three levels of intensity (light, moderate and high) for each activity. As a result, the percentages of overlap between various physical activities increased, and the results were split into three main groups, which included: physical activities with high consistency of amplitude and frequency; Physical activities with overlapping of amplitude and frequency; physical activities with inconsistent amplitude and frequency values.

5.3.2 Physical Activity with High Consistency

The physical activities with high consistency of amplitude and frequency measures are cycling, rowing, and running, allowing the system to clearly differentiate these activities from other physical activities. For example, stationary cycling is recognised with a high accuracy level owing to the high spectrum frequency consistency with slight overlap in amplitude measures with other physical activities. Figure 5.10a shows the frequency and amplitude of five participants of different ages (P1=20 years, P2=48 years, P3=60 years, P4=70 years and P5=80 years) who performed the cycling activity at low moderate and high intensities.

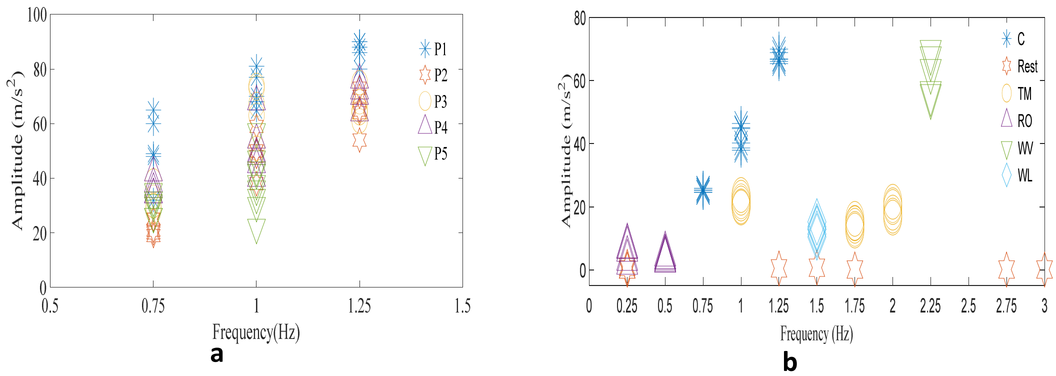


Figure 5.10. **a.** Power spectrum amplitude and frequency measures for five participants of different ages performing cycling at low (0.75 Hz), moderate (1 Hz) and high (1.25 Hz) intensities. **b.** Power spectrum amplitude and frequency measures from four different activities with different intensities.

It can be clearly observed from Figure 5.10a that the dominant frequency for all participants was 0.75 Hz for light, 1 Hz for moderate, 1.25 Hz for vigorous intensity. The only patient that did not produce a frequency for vigorous intensity was P5, who was unable reach 90 rpm owing to limited coordination. Although amplitude measures of the dominant frequency were easy to identify for the three intensities, there was a slight overlap in the amplitude measures for moderate and vigorous cycling, which had a minor impact on the activity recognition. The consistency of frequency measures for the three levels of cycling intensity was reflected by an overall accuracy of 90%. Figure 5.10b shows the frequency and amplitude data at rest and from five different physical activities (CL, TM, RO, WV, and WM) performed by different participants at different levels of intensity. There is no overlap in frequency and amplitude between most activities except the dominant frequency of moderate CL and TM where there is no clear difference in amplitude. Rest (inactivity) could also be clearly identified from other activities. For example, the frequency of the power spectrum during rest ranged from 0 to 5 Hz. However, the amplitude was always less than 1 m/s^2, clearly distinguishing rest from any other physical activity.

5.3.3 Physical Activities with Overlapping of Amplitude and Frequency

Physical activities with high consistency and significant overlapping on both amplitude and frequency, included CTL, CTM, WL, CL, RO, and LP (Figure 11a) resulting in the system being unable to clearly distinguish between some of these activities. Even though there was overlap in spectral measures for these activities, the system was still able to record this data as accumulated gain and time but lacked accuracy at identifying the specific type and intensity of activity. For example, the system could detect a patient performing TMV as either CL or WL. This resulted in the system lodging an incorrect gain value of 0.75 (CL or WL) when it should have been 2 (TMV).

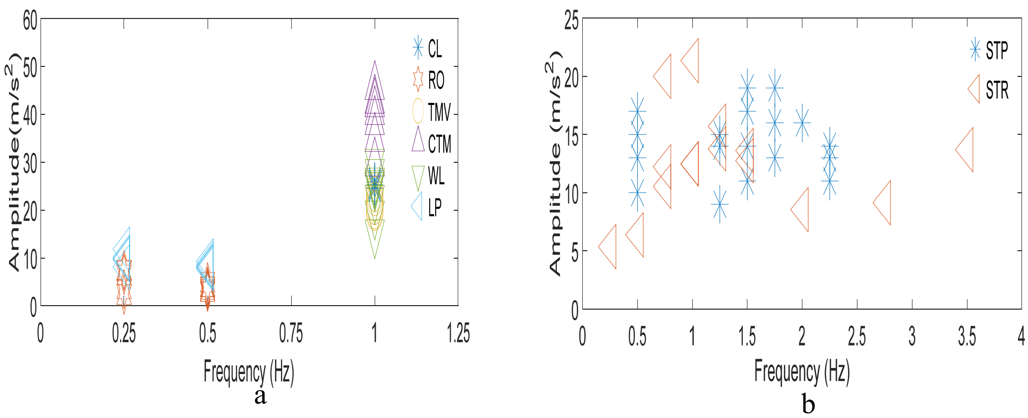


Figure 5.11. a and b. Overlapping of amplitude and frequency measures between different physical activities.

5.3.4 Inconsistent Values of Physical Activities

Staircase ascending/descending, and step-up were the two activities that showed inconsistency in both amplitude and frequency. Figure 5.11b shows that both of these activities produced highly variable amplitude and frequency measures, leading to overlapping with other activities, and impacting the accuracy (activity recognition and gain calculation) of the system.

Different physical activities have some overlap with each other. This overlap leads to some activities not being recognised, and this may result in the loss of some credited effort. The special logical approach design is implemented on Raspberry Pi using Python code to enhance the activity recognition and credit the physical effort calculations as explained in Section 4.3. To reduce the impact of overlap of power spectrum frequency and amplitude measures among recognised activities, the extracted recognised activities are examined using four methods based on short-term history data. Those methods concurrently process the data and store the results in a separate output file. Tests on these methods are discussed in section 5.4.1.

5.4 Gateway Code Features.

The gateway code was designed and implemented to support the mixed mode prehabilitation programme in terms of multi-sender (WSD) data receiving and analysis, activity recognition, short-term data repository, detecting the key elements and boundaries of the mixed mode prehabilitation model, calculating the accumulated time and gain and then sending the whole processed data to the Cloud TS for further analysis, long term repository (Prehabilitation program wide), and visualisation. Figure 5.12 shows the basic architecture and features of the IoT gateway.

The first feature that prepares the receiver for the incoming data is called initial alisation. During this stage, all the data buffers and basic parameter variables are initialised, the data queue is constructed, and the data output filename is made according to the current date. This naming of the file according to the data helps to make a new file for everyday data logging to avoid losing complete set of data in case the file is corrupted, and the gateway fails to send processed data to the cloud. In addition, for easy monitoring and controlling efforts on day-by-day basis, the accumulation in time and gain is reset every day at 24:00. In the proceeding section, the code checks for the output data file in the output directory.

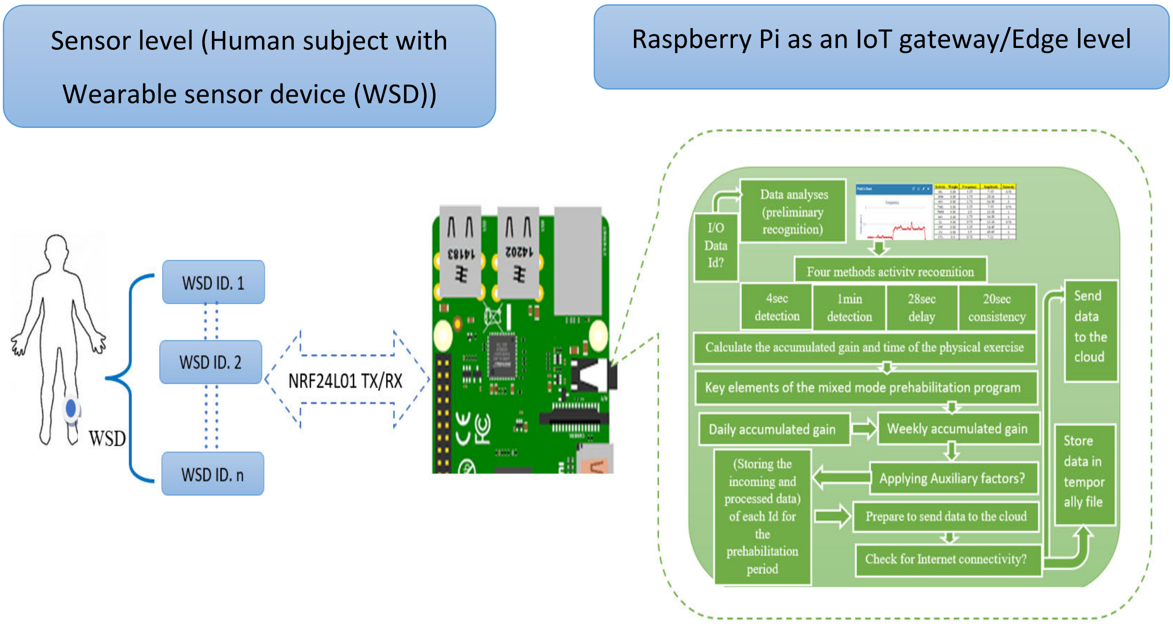


Figure 5.12. Gateway architecture and feature for handling and processing multi-sender WSD data.

The second feature is related to ensuring the Internet connection. The Raspberry Pi will always attempt to send data to the cloud. The embedded software continuously checks the connections between the gateway and cloud (Pi sending the request and receive the response).

Once the gateway detects a miss connection a CSV file is created to store and uploaded data. Once the CSV file is opened, all the data, along with their original timestamps, are loaded in the queue, as shown in Figure 5.13. In this manner, the system maintains the timestamp and the sequencing of the data. This process will continue until Pi received positive response that the connection has been established.

Node Id	Date	Time	Amplitude (m/s^2)	Frequency (Hz)	Code of activity Recognition	Accumulated Time of each WSD	Accumulated Gain of Each WSD	ThingSpeak API Key	ThingSpeak channel ID
2	2021-08-04	19:21:33	14.38	0.75	11	0.01333	0.00335	0G6PAH7KD	51383
0	2021-08-04	19:21:33	12.93	1.5	2	2.13333333	0.0536	233TUBX2W	4957
3	2021-08-04	19:21:35	0.07	0.25	0	0.66666667	0	PO66I4OX5	20023
1	2021-08-04	19:21:36	22.87	1.75	7	1.53333333	0.0132	HYV4OWYE6	6247
0	2021-08-04	19:21:37	14.21	1.5	2	0.1333	0	233TUBX2W	4957
2	2021-08-04	19:21:38	17.82	0.75	11	0.02666	0.005025	0G6PAH7KD	51383
1	2021-08-04	19:21:39	22.77	1.75	7	1.6	0.0264	HYV4OWYE6	6247
3	2021-08-04	19:21:40	0.08	3	0	0.73333333	0	PO66I4OX5	20023
0	2021-08-04	19:21:41	15.22	1.5	2	2.26666667	0.00165	233TUBX2W	4957
2	2021-08-04	19:21:42	15.27	0.75	11	0.03999	0.0067	0G6PAH7KD	51383

Figure 5.13. Full details of accumulated data per channel stored in 'not synced' CSV file in case of lost Internet connectivity.

The third feature related to the Internet connectivity is re-establishing. Through this, the data stored in the CSV file (Figure 5.13) is uploaded first followed by the upload of live feed of data. This script uses threading and makes two threads for multiprocessing. The first thread is for the handling of the data coming from the WSD, all four methods, the logging of the data, and the storing of the data in CSV file. The second thread is for uploading the available data to the cloud TS, as shown in Figure 5.13. Once the Internet connectivity is confirmed, the basic header of the data is constructed in the form of a string, and the main buffer is initialised. As in the queue, the data are gathered from different nodes, and thus, it is necessary that the system can sort the data according to different nodes to send the data to their respective channels (Figure 5.13). Once this sorting is done, and the main buffer list is constructed with the data of all nodes, uploading is performed. The upload performed here is a bulk upload in which the system can upload 900 data frames in a single request as shown in Figure 5.14. Any two consecutive bulk upload requests for the same channel should be separated by a time frame of 15 seconds, otherwise, the server will reject the data.

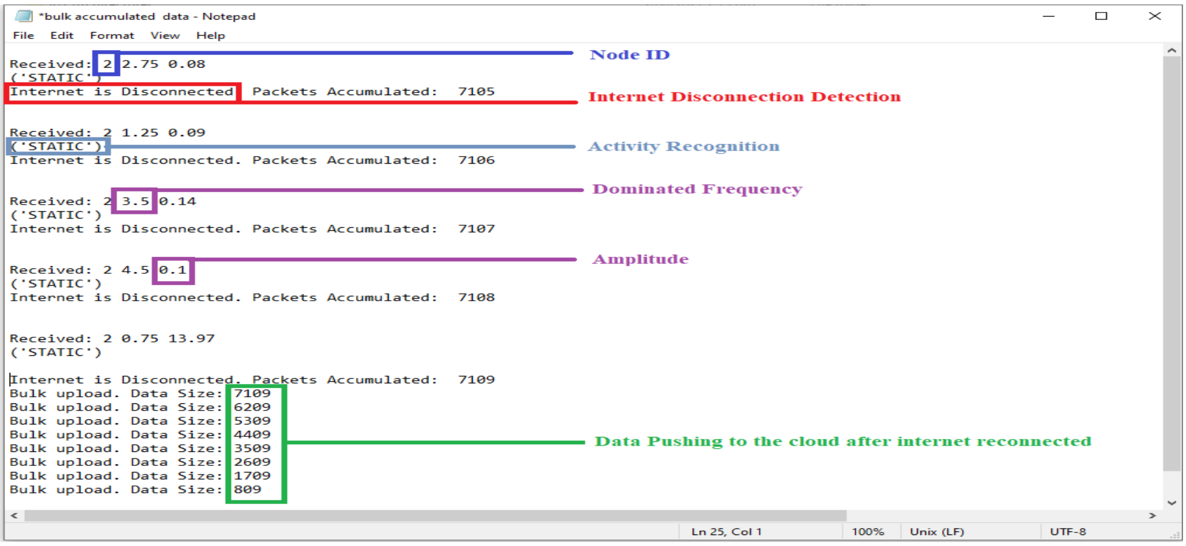
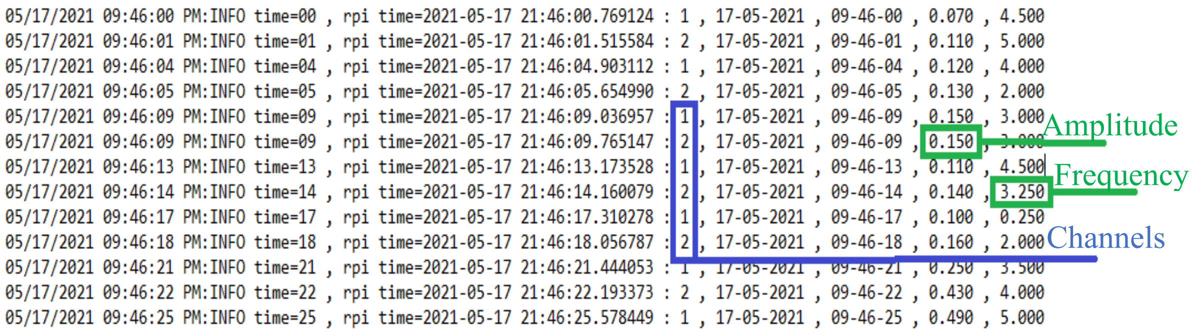


Figure 5.14. Accumulated bulk of upload 900 data frame each request after the Internet connection is established.

The fourth feature that is the capability of multi-node receiver. The protocol used to transmit the data is 'NRF24_Network'. In this protocol, each WSD is given a node ID address, as shown in Figure 5.15. The code receives the data from the NRF24 transmitters and accumulates the data in a local buffer, which is used to produce the data for all the four methods, and then to save in a separate sub-sheet according to the node ID address. After receiving the data, scripts are checked for any false values. If the data received follow the syntax and range of real or acceptable data, then they are processed further by the program, otherwise, a 'none acknowledged' message is sent to the WSD for sending the data again.



```
05/17/2021 09:46:00 PM:INFO time=00 , rpi time=2021-05-17 21:46:00.769124 : 1 , 17-05-2021 , 09-46-00 , 0.070 , 4.500
05/17/2021 09:46:01 PM:INFO time=01 , rpi time=2021-05-17 21:46:01.515584 : 2 , 17-05-2021 , 09-46-01 , 0.110 , 5.000
05/17/2021 09:46:04 PM:INFO time=04 , rpi time=2021-05-17 21:46:04.903112 : 1 , 17-05-2021 , 09-46-04 , 0.120 , 4.000
05/17/2021 09:46:05 PM:INFO time=05 , rpi time=2021-05-17 21:46:05.654990 : 2 , 17-05-2021 , 09-46-05 , 0.130 , 2.000
05/17/2021 09:46:09 PM:INFO time=09 , rpi time=2021-05-17 21:46:09.036957 : 1 , 17-05-2021 , 09-46-09 , 0.150 , 3.000
05/17/2021 09:46:09 PM:INFO time=09 , rpi time=2021-05-17 21:46:09.765147 : 2 , 17-05-2021 , 09-46-09 , 0.150 , 3.000
05/17/2021 09:46:13 PM:INFO time=13 , rpi time=2021-05-17 21:46:13.173528 : 1 , 17-05-2021 , 09-46-13 , 0.110 , 4.500
05/17/2021 09:46:14 PM:INFO time=14 , rpi time=2021-05-17 21:46:14.160079 : 2 , 17-05-2021 , 09-46-14 , 0.140 , 3.250
05/17/2021 09:46:17 PM:INFO time=17 , rpi time=2021-05-17 21:46:17.310278 : 1 , 17-05-2021 , 09-46-17 , 0.100 , 0.250
05/17/2021 09:46:18 PM:INFO time=18 , rpi time=2021-05-17 21:46:18.056787 : 2 , 17-05-2021 , 09-46-18 , 0.160 , 2.000
05/17/2021 09:46:21 PM:INFO time=21 , rpi time=2021-05-17 21:46:21.444053 : 1 , 17-05-2021 , 09-46-21 , 0.250 , 3.500
05/17/2021 09:46:22 PM:INFO time=22 , rpi time=2021-05-17 21:46:22.193373 : 2 , 17-05-2021 , 09-46-22 , 0.430 , 4.000
05/17/2021 09:46:25 PM:INFO time=25 , rpi time=2021-05-17 21:46:25.578449 : 1 , 17-05-2021 , 09-46-25 , 0.490 , 5.000
```


Figure 5.15. Raspberry Pi logfile showing the TX/RX time, node ID, amplitude, and frequency.

5.4.1 Activity Recognition-Outlier Filter

This section discusses the four methods used to filter out the misrecognised movements of various physical activities. The four logical recognition methods indicated as M1, M2, M3 and M4 are integrated with the gateway functions. Six consecutive minutes of physical movements were randomly selected and used to illustrate the mechanism of activity recognition. Figures 5.16 (a, b, c and d) demonstrate the ability of four recognition methods to identify various physical activities throughout the six minutes. As discussed previously, M1 recognises and calculates the efforts every 4 seconds based on the FFT result. Figure 5.16 a. illustrates M1 behaviour during the selected six minutes of physical activity. In the first minute, M1 could recognise 73% of the actual activity. Starting from Rest to CL, transitions produced inconsistent data values for 16 seconds, after which the output data values are stabilised at the CL. Accordingly, the recognition percentages for M1 would be affected, and the same procedure would be applied to the entire period. Meanwhile, M2 failed to recognise activity in the first minute; this has been depicted in Figure 5.16 b. As discussed in Chapter 4, the M2 technique is based on the storing of 15 incoming readings in a separate buffer and recognising them according to the buffer data consistency. A threshold data of 80% consistency is the minimum used in this example for correction purposes. Any consistency below this threshold will result in discarding the correction. M2 fails to recognise activity when the buffer data remains below 80%. Figure 5.16 c. shows M3 activity recognition techniques. While M3 carries out the same action as M2, the former allows for a delay of 28 seconds to cover the transition times between the activities. Although this technique succeeds in covering the transitions between the first and second, third and fourth, and fifth and sixth minutes, it fails to cover the second to third, and fourth to fifth minute transitions. There are two primary causes for the decreased recognition percentages. To begin with, switching between activities results in data variations. Additionally, the M3 buffer threshold level was set the same as the buffer threshold level of M2. Consequently, they fail to carry out the recognition process in case the number of conflicting data points per buffer exceeds three. Secondly, the 28-second delay may seem excessively long to some individuals while it may seem quite short to others. For instance, the subject in this test required 16 seconds to obtain steady state measurements, whereas 28 seconds was insufficient for the elderly patients. To address this issue, the threshold may be set to 60% instead of 80%, and the delay be set to 20 seconds instead of 28 seconds. As illustrated in figure 5.16 c, these two adjustments will improve the recognition capability of M3, which can accurately recognise all six minutes of a period. Further investigation is necessary, as the switching period between activities for patients vary based on multiple factors including age and level of fitness. The recognition activity of M4 has been demonstrated in Figure 5.16 d. As discussed previously, the buffer length took five readings every 20 seconds. Accordingly, each minute was divided into three equal parts. In the first 20 seconds of the physical activity, M4 detected different activities with inconsistent buffer readings. However, in the second and third parts of the first minute, M4 detected the actual activity with a recognition success of 100%. Therefore, the first minute recognition accuracy percentages per each one-third minute would be as follows: (0, 100%, 100%). The total percentages for the first minute are 67%. The main advantage of M4 is its capability in achieving high recognition percentages with such inconsistency readings while avoiding the loss of entire minutes, while in M2 and M3, the entire minute of recognition is lost when the reading consistency falls below 80%.

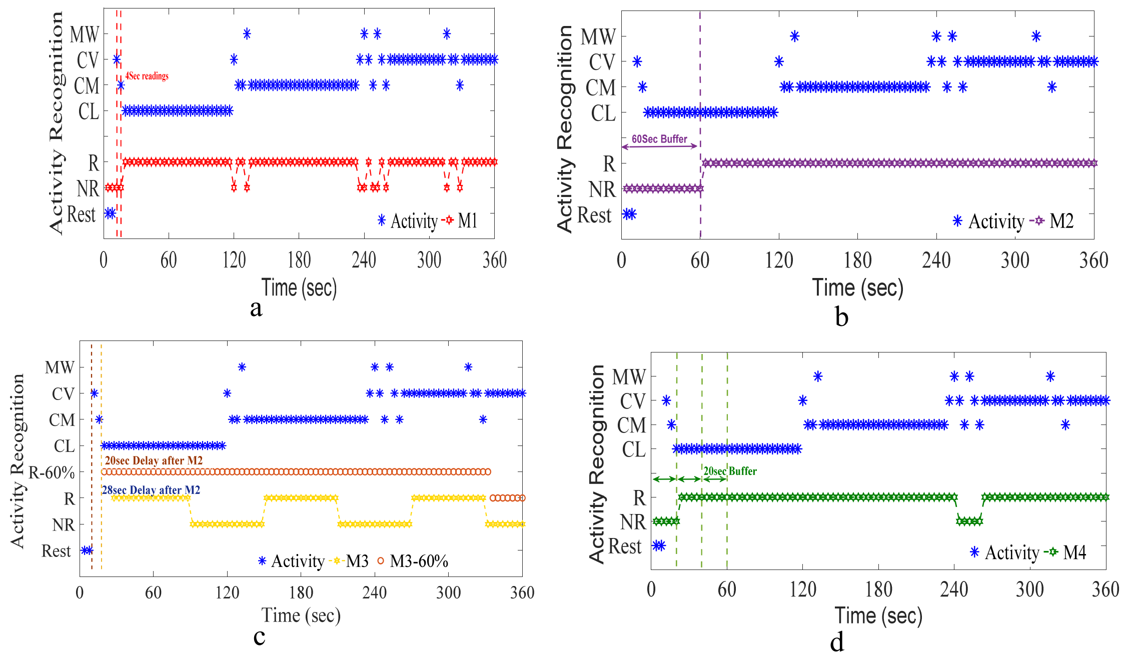


Figure 5.16. Four methods of activity recognition **a.** M1, **b.** M2, **c.** M3, **d.** M4.

Here, R represents 'recognised', and NR represents 'non-recognised'.

Table 5.3 illustrates the six-minute outcomes of the four techniques used, in terms of accumulated time, gain and recognition percentages. The 100% per minute indicates full gain and time, and 0% indicates zero gain and time, while the other percentages are direct reflections of the time and gain values (i.e., with 67%, time will be 40 seconds out of 1 minute, with a gain of 0.0168 out of 0.0251). Inferring from the above discussion, there exists a linear link between activity recognition and accumulated time and gain.

Table 5.3. Illustrates the four activity recognition methods in terms of time, gain and percentages.

Method (M)	Accumulated time(sec)	Accumulated gain	Activity Recognitions (%)	Period
M 1	43.8	0.0184	73	1st minute
M 2	0	0.0000	0	
M 3	60	0.0251	100	
M 4	40.2	0.0168	67	
M 1	55.8	0.0234	93	2nd minute
M 2	60	0.0251	100	
M 3	0	0.0000	0	
M 4	60	0.0251	100	
M 1	55.8	0.0312	93	3rd minute
M 2	60	0.0335	100	
M 3	60	0.0335	100	
M 4	60	0.0335	100	
M 1	51.6	0.0288	86	4th minute
M 2	60	0.0335	100	
M 3	0	0.0000	0	
M 4	40.2	0.0307	67	
M 1	48	0.0268	80	5th minute
M 2	60	0.0335	100	
M 3	60	0.0335	100	
M 4	60	0.0335	100	

The average activity recognition percentages and cumulative gains for each method have been summarised in Table 5.4. According to the table, M4 values were found to be greater than those of other methods, with higher percentages of activity recognition. While M1 is the runner-up to M4 in terms of achieving higher values on gain and recognition percentages, short time tests of three physical activities with 28-second delays deem M3 incapable of covering the three intensity levels for the three transitions in five minutes. Therefore, as per the current threshold and delay settings, M3 is regarded as an ineffective short-term recognition technique. Hence, at this stage M4 determined the activity recognition each 20 sec individually rather than one minute as in M2 and M3. Accordingly, the accumulated time and gain are calculated per 20 sec as showed in Tables 5.3 and 5.4. In other words, the recognition and misrecognition will impact on 1/3 of minute in each time.

Table 5.4. shows accumulated gain and average percentages over the five minutes.

Method	Accumulated gain	Average activity recognition %
M1	0.129	85
M2	0.126	80
M3	0.092	60
M4	0.140	87

5.4.2 Fine Tuning the Non-Personalised Database

Individuals eligible to participate in the prehabilitation programme have varying levels of fitness, body mass index (BMI), height, age group, health conditions and cadence of movement. Thus, data parameters are certain to differ across the participants. As previously stated, data parameters (amplitude and frequency) are the core determinants of activity recognition, as each recognition method primarily depends on these values. For instance, M1 recognition techniques determine which data is to be employed based on a comparison between the database and the incoming data (amplitude and frequency). Table 5.5 demonstrates the data for two common physical activities prescribed to the participants of the prehabilitation program, represented as CM and WM. Data were collected from the six participants, each patient differing in age group, fitness level and health condition. To explore the impact of the categorised database on the accuracy percentages of activity recognition, it is necessary to analyse each individual's data parameters. For instance, when the young, healthy subject engaged in CM physical activity, the amplitude range is of 65-80m/s^2, while the amplitude ranges of the remaining participants are of lower levels, negatively affecting the activity recognition. However, expanding the amplitude or frequency range to cover another individual parameter value will create issues of overlap between the activities. The same would apply to WM. Variation in cadences and inconsistencies in walking speed result in a comparable frequency of variance results. For example, two senior volunteers (aged 77 and 80 years) were unable to sustain their walking speed. In such a case, the outcome data would show fluctuations at the corresponding frequency while the amplitude range would remain within the normal range of values. In this scenario, the amplitude indicator would perform better than the frequency indicator in terms of activity recognition approaches. In conclusion, both the consistency of the frequency component and the narrow range of the amplitude contribute to an increase in recognition percentages.

Table 5.5 illustrates the data parameters for different participants.

Age	Gender	Health condition	Fitness level	Activity	Amplitude (m/s^2)	Frequency (Hz)
20 (P1)	Male	Healthy	Fit	CM WM	65-80 28-40	1.25 2.25
51 (P2)	Male	Healthy	Fit	CM WM	36-50 23-35	1.25 2
67 (P3)	Female	Healthy	Fit	CM WM	32-38 15-26	1.25 1
71 (P4)	Female	Healthy	Fit	CM WM	29-41 12-22	1.25 1.5
77 (P5)	Male	Unhealthy	Unfit	CM WM	34-50 11- 26	1.25 1.25-1.75
80 (P6)	Male	Unhealthy	Unfit	CM WM	26-35 16-28	1 1.5-3

Refer to Table 5.5, where the range of the CM physical activity of young participants is shown to be extremely higher compared to other participants, while the level of middle-aged CM data parameters lies between that of the young and elderly participants. Refer to Figures 5.17 and 5.18 for a detailed view of the CM and WM data ranges. Figure 5.17 illustrates three to four main categorised databases that were extracted based on the participants' outcome data. In the first group, participants P3 and P4 were clustered together, with an amplitude range of 29-41m/s^2 and an amplitude bandwidth of 15 m/s^2. An additional database could be added to this group for P6, as the amplitude range 26-35 m/s^2 is nearly within the P3 and P4 ranges. The second group of participants, P5 and P2, had an amplitude range of 34-50 m/s^2 with an amplitude bandwidth of 16 m/s^2. Finally, the third database group consisted of the healthy young participants, P1, with an amplitude range of 65-80 m/s^2 and an amplitude bandwidth of 15 m/s^2.

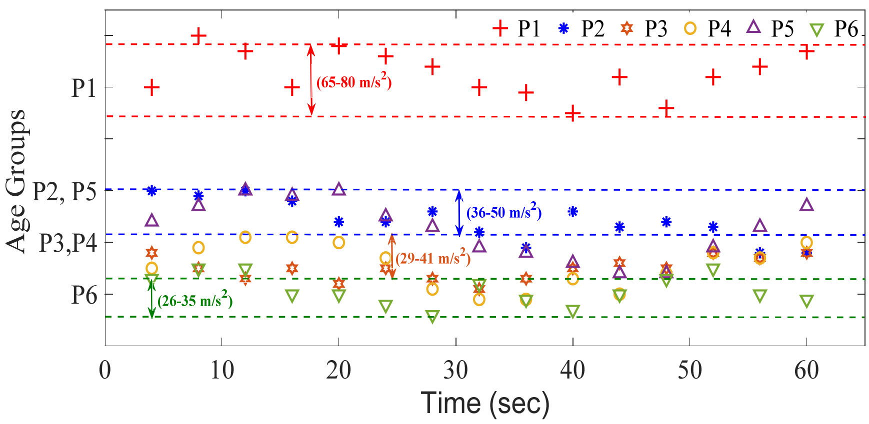


Figure 5.17. shows the CM physical activity parameter levels based on age groups.

Additionally, WM data parameters are categorised into two groups for the same participants, as shown in Figure 5.18 below. The first group with the participants P3, P4, P5, and P6, has an amplitude range of 11-28 m/s^2 and an amplitude bandwidth of 17 m/s^2. The second group of participants, P1 and P2, had amplitudes ranging from 23–40 m/s^2 and bandwidths of 17 m/s^2. Based on Figures 5.17 and 5.18 a categorised database can be created based on age group and fitness level. Categorised database could reduce the physical activity miss recognition percentages by reducing the overlapping between different physical activities, by narrowing amplitude and frequency swing bands. This will work as an additional tunning to the recognition methods (M1-M4).

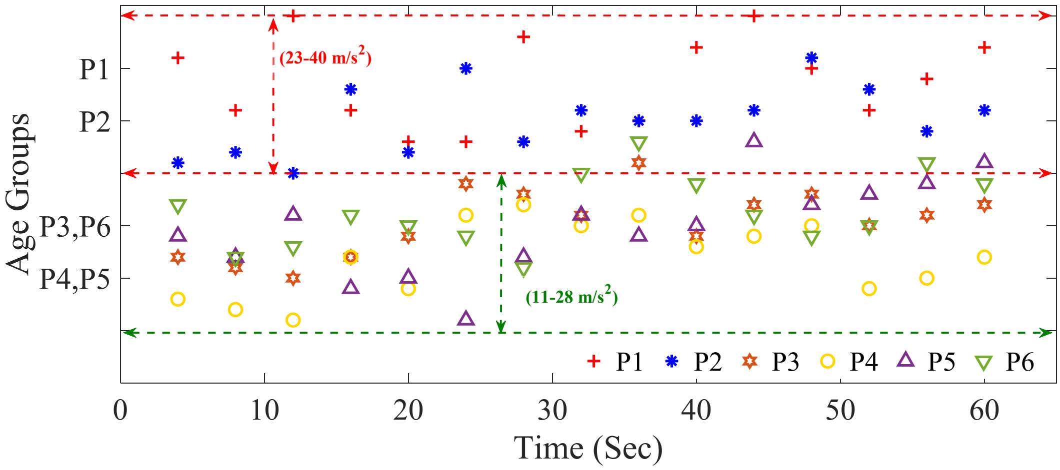
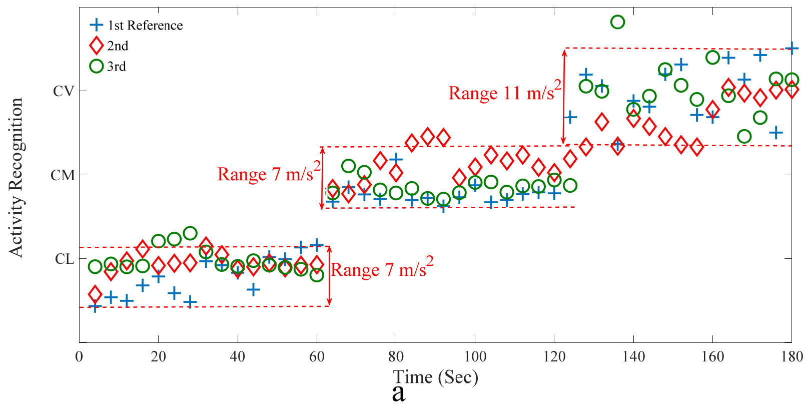


Figure 5.18. Shows the WM physical activity parameter levels based on age groups.

As discussed earlier in Chapter 4 Section 4.2.1, a non-personalised database (shared database) was created using data gathered from multiple participants (patients) and organised based on the similarities of the data parameters among them. This type of database has two main advantages: first, it shows how far the system recognition techniques are from the actual physical activity performed by a patient in a real-life scenario. Second, for system training purposes, in other words, the new incoming data added to the non-personalised (shared) database will enrich the database bank and that will reflect positively on the activity recognition performance.

Another type of database could be called a personalised database (which is collected from the same individual performing the same activities at different times). Several iterations of recording data from the same subject are acquired while performing the same activity at different times and dates. Fine tuning in the storing database based on new incoming data will significantly improve the performance of activity recognition. Figures 5.19 a and b shows different intensity levels (low, moderate, and vigorous) of cycling physical activity performed by a middle-aged male subject. The subject was requested to do the same activity during his three visits to the AUT physiotherapy gymnasium. Figures 5.19 a and b illustrate the first visit readings assigned as a reference database for this subject in terms of amplitude and frequency, respectively. The readings of the second and third visits were compared with the reference reading. Figure 5.19 a. shows the amplitude ranges for the three different intensities are almost between 7 m/s^2 for low and moderate, while a little bit higher in vigorous intensity, but almost 2/3 of categorised database band for the same activity and intensity. As mentioned previously, a narrow band of amplitude and consistency in corresponding frequency leads to reduce the overlapping with other activity. Figure 5.19 b. shows same activity in terms of frequency components. However, inconsistent reading does not have a significant effect on activity, and for example, according to M2 and M4, the error percentages in terms of activity recognition are almost zero. Accordingly, personalised database may consider the best solution for the mixed mode prehabilitation program in terms of activity recognition and efforts calculations.



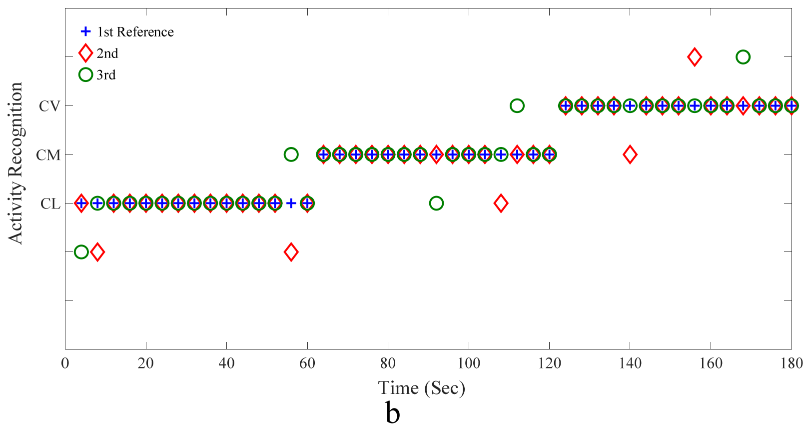


Figure 5.19. Show the CL, CM, and CV physical activity parameter levels based on Personalised activity recognition **a.** Amplitude parameter, **b.** Frequency Parameter.

The average outcome of each type of database in terms of percentages in activity recognition can be seen in Table 5.6. A personalised, categorised, and non-personalised database was recruited as a reference for the three common activities in the prehabilitation programme (cycling, rowing, and walking). Referring to Table 5.6, three participants' (P2, P4, and P5) databases were tested based on three types of databases in terms of activity recognition techniques (M1, M2, and M4). M3 was eliminated from this test due to the arbitrary selection of participant data. Table 5.6 illustrated that that the system performance shows high percentages in terms of activity recognition when recruiting a personalised database; whereas recognition percentages dropped significantly in non-personalized databases, particularly in walking activity, for a variety of reasons that have already been discussed. A categorised database, on the other hand, produces acceptable results that are slightly less than personalised but far superior to non-personalised databases.

Table 5.6 Shows activity recognition percentages based on three database types.

Participant's age	Physical activity	Personalised (%)	Categorised (%)	Non-Personalised (%)
51 (P2)	CM	92.5	84	75
	ROL	90	83	76
	WM	78	69	60
71 (P4)	CM	92	86	73
	ROL	90	86	76
	WM	75	68	54
77 (P5)	CM	90	81	72
	ROL	88	83	79
	WM	71	60	51

Figure 5.20 shows the average activity recognition percentages for two physical activities, CM and WM, as reflected in Table 5.6. It is clearly stated that high percentages of activity recognition are found with a personalised database. The lowest recognition performance was with non-personalised databases. Hence, to avoid congestion, ROL was eliminated from this graph.

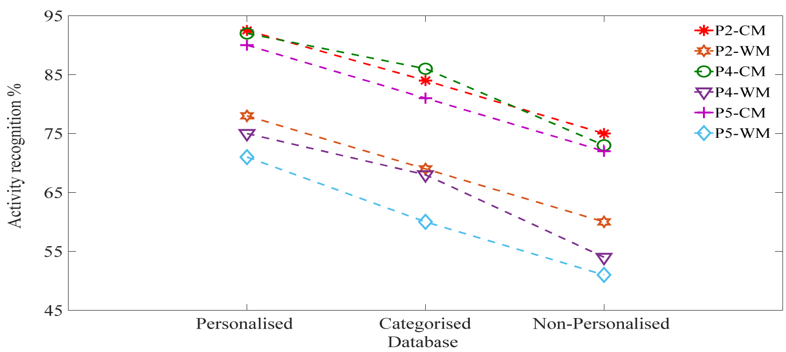


Figure 5.20 Activity recognition based on three types of databases.

5.4.3 Multi Factors of Activity recognition-outlier filter

According to the previous subsections (5.4.1 and 5.4.2), the activity recognition percentages of different methods are significantly affected by different factors. For example, the direct method is quite affected by the time delay of incoming data and precision of non-personalised databases; while buffer consistency threshold setting (80% in this study), and database type have a significant impact on M2 and M3. In addition, M3 has an additional factor that could impact the activity recognition percentages, which is time delay (28 sec set as the time delay in this study). According to the M4 techniques which were described earlier, buffer size could be the only factor that could impact on the activity recognition percentages. The threshold value, buffer size, and M3 time delay were all arbitrarily selected. For example, the 80% threshold was chosen to offer high biases and certainty to activity recognition. While the system has the ability to deal with different threshold levels, as will be discussed later in this section, one minute of buffer size is considered enough time to collect and decide the 15-reading data type based on M2 and M3. For the elderly patient, the delay time was considered a reasonable time to switch from a certain intensity to another intensity level within the same physical activity. There is also flexibility in selecting the buffer size and time delay in this system, which can be changed based on fitness level or age group. A young fit person, for example, requires much less time than 28 seconds to switch from one intensity level to another while performing the same physical activity. Based on the above, the data of the participants (young, elderly healthy, and elderly patients) that has been collected for different physical activities will be retested according to the above factors to estimate the beast results without the effect of the system performance in terms of accumulated time and gain. Cycling and walking are the common activities that were done by all participants. Then, both physical activities will be the reference for all recognition methods. For the M1, the time delay factor has been discussed earlier in section 5.2, and [42] found the optimum delay was 4 sec. All the other methods' results are largely determined by the outcome of M1. As a result, the 4 sec delays will not be discussed during this session. Table 5.7 demonstrates the average values of activity recognition of cycling and walking physical activities with different intensities for 35 participants with different age groups and different fitness levels based on the M1 method. To avoid the needless repetition of data presentation, the categorised database was not used in the methods (M1, M2, and M4); Personalised and non-personalised databases were recruited in M1 only. The results show that M1 gains high recognition percentages of cycling activity for all age groups (G1-G4) on both personalised and non-personalised databases. While the recognition percentages for walking activity for personalised and non-personalised databases are roughly 70% and 60%, respectively; the reason behind that will be explained in detail in Chapter 6 in the results discussion.

Table 5.7 shows personalised and non-personalised database according to M1.

Participants groups	Personalised Cycling	Non personalised Cycling	Personalised Walking	Non personalised Walking
G1(Young Healthy)	91	75	79	69
G2 (Middle age Healthy)	93	80	76	60
G3 (Elderly Healthy)	90	83	71	59
G4 (Elderly patient)	88	76	68	55
Average %	**90.5**	**78.5**	**73.5**	**60.75**

Table 5.8 shows M2 activity recognition performance when the threshold levels of the data buffer consistency decrease or increase. The results show the high percentages of physical activity for both the personalised and non-personalised are high when the threshold level is reduced to 60% and 65%. While the percentages are reduced significantly when the value is increased, the threshold level is between 90% and 95%. The same test has been repeated on M3 with a reduced time delay of 20 sec. The recognition results have been significantly enhanced and are almost the same as M2 results for the threshold levels (60–75%). The percentage results of M3 are strongly impacted (around half of the M2 results), when the threshold level is increased to 90-95 percent; it is due to M3's failure to cover the transition area in some cases.

Table 5.8 Shows personalised and non-personalised database based on M2.

Threshold %	Personalised Cycling %	non-Personalised Cycling %	Personalised Walking %	non-Personalised Walking %
60%	97	91	83	76
65%	96	87	77	72
70%	93	81	81	69
75%	90	78	74	64
80%	86	73	70	58
85%	81	70	63	51
90%	69	54	52	43
95%	56	43	48	37

On the other hand, Table 5.9 demonstrated the effect of the buffer size on the M4 method. The recognition percentages show that the optimum buffer size value is 20 sec for both personalised and non-personalised databases.

Table 5.9 Shows M4 recognition percentages based on buffer size.

Buffer size (sec)	Personalised Cycling %	non-Personalised Cycling %	Personalised Walking %	non-Personalised Walking %
32	84	78	73	64
28	84	79	73	65
24	92	84	75	69
20	96	88	80	74
16	82	74	70	56
12	64	58	55	43

5.5 Cloud-Based Platform

ThingSpeak (TS) is an Internet based open application programming interface (API) IoT source information platform that has quite a wide range of gateway and sensor data to store. As discussed in section 5.2, the processed data in the gateway is sent to the cloud IoT TS platform using the HTTP protocol, along with the amplitude and frequency extracted from the WSD. The TS application is used for storing, retrieving, and analysing live data from different sensors. It is treated as a platform for aggregating the sensor data and processing the same using MATLAB software for further data analysis and visualisation. An additional feature that the TS can perform which is Thing Tweet such as programming TS channel for limited value. When a value exceeds the limit, an automatic Tweet alerts users or healthcare support. All these features have been used in this design to support the mixed mode prehabilitation programme such as visualising the real-time incoming data from the gateway as shown in Figure 5.21. Using the information available inside the cloud repository and utilising the typical processed and activity information, a presentation is created (see Figure 5.21). The first two plots symbolise (a and b) the compressed parameters, i.e., maximum amplitude, corresponding frequency, while the third and fourth graphs (c and d) represent the accumulated time and gain.

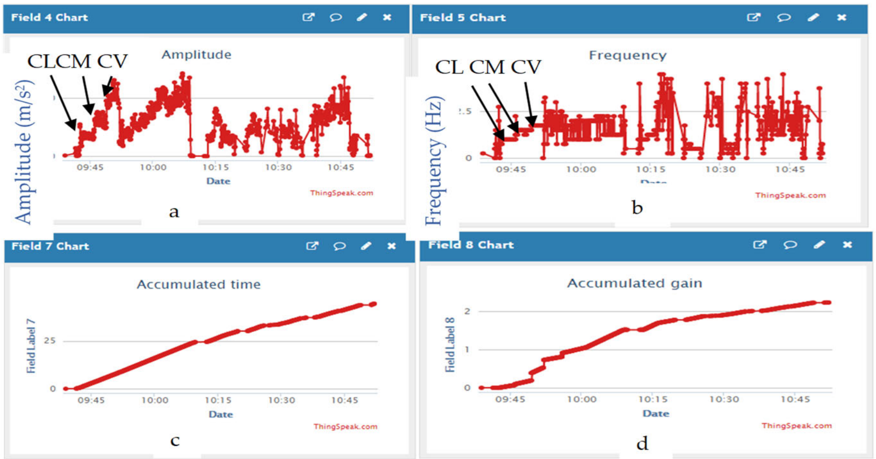


Figure 5.21. Cloud data visualisation for both WSD data **(a and b)** and gateway processed data **(c and d)**

The long-term repository and data analysis can be seen in Figures 5.20 a and b, by retracing the storage data for a certain time for further analysis. The flexibility in data retrieving and further processing will support the clinician team in terms of real time and history monitoring during mixed mode prehabilitation program. For example, Figure 5.22 a, showing data for one hour session of physical activity, has been retrieve, by using MATLAB software as the MATLAB is the media of TS platform. MATLAB has the ability to merge the vital processed data in a single graph for active visualization. Figure 5.20 b shows the zoom in of a certain time period for this session.

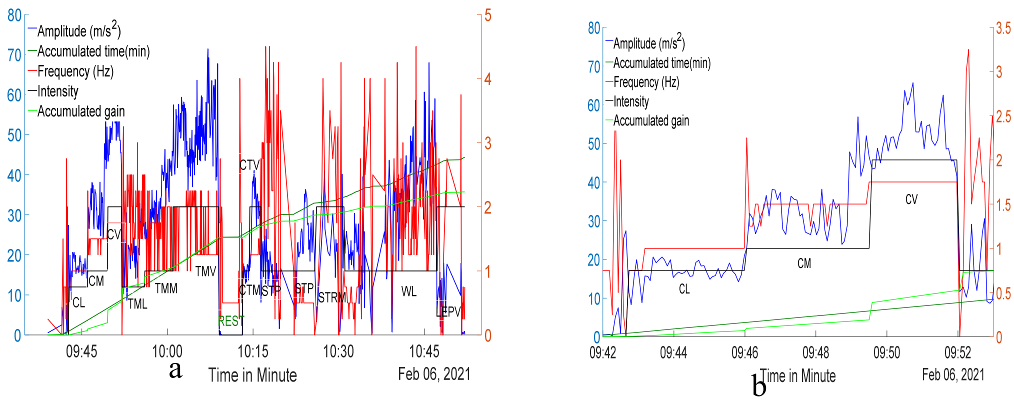


Figure 5.22. a. Retracing data and applying different analysis methods, **b.** Time windows for cycling activity at low, moderate, and vigorous intensity.

The typical TS has eight separate channels, and each channel has eight data fields used to store the incoming data from the gateway (Raspberry Pi). In this study, the received data from Raspberry Pi spread across all the eight available fields (Field 1: Node ID, Field 2: Date, Field 3: Time, Field 4: Maximum amplitude, Field 5: Corresponding frequency, Field 6: Code of activity recognition (CAR), Field 7: Accumulated time, Field 8: Accumulated gain). The incoming data stored in the TS cloud repository are in three different formats, i.e., JSON, XML, and CSV. The pattern screenshot of the information layout saved in CSV across areas 4, 5, 6, 7, and 8 can be seen in Figure 5.23.

created_at	entry_id	field1	field2	field3	field4	field5	field6	field7	field8
2021-08-02 20:17:17 NZST	1	0	2/08/2021	20:17:17	3.06	0.5	17	0.0667	0.00267
2021-08-02 20:17:33 NZST	2	0	2/08/2021	20:17:33	12.92	0.75	8	0.3333	0.0113
2021-08-02 20:17:38 NZST	3	0	2/08/2021	20:17:38	11.36	0.75	8	0.4	0.01295
2021-08-02 20:17:42 NZST	4	0	2/08/2021	20:17:42	15.51	0.75	8	0.4667	0.01515
2021-08-02 20:17:46 NZST	5	0	2/08/2021	20:17:46	13.25	0.75	8	0.5333	0.01
2021-08-02 20:17:50 NZST	6	0	2/08/2021	20:17:50	10.91	0.75	8	0.6	0.019
2021-08-02 20:17:54 NZST	7	0	2/08/2021	20:17:54	12.26	0.75	8	0.6667	0.02065
2021-08-02 20:17:58 NZST	8	0	2/08/2021	20:17:58	10.28	0.75	8	0.7333	0.02065
2021-08-02 20:18:02 NZST	9	0	2/08/2021	20:18:02	14.17	0.75	8	0.8	0.02065

CAR

Cloud created date and time WSD node ID Data cloud entery date and time Amplitude and Frequency Accumulated Time and Gain

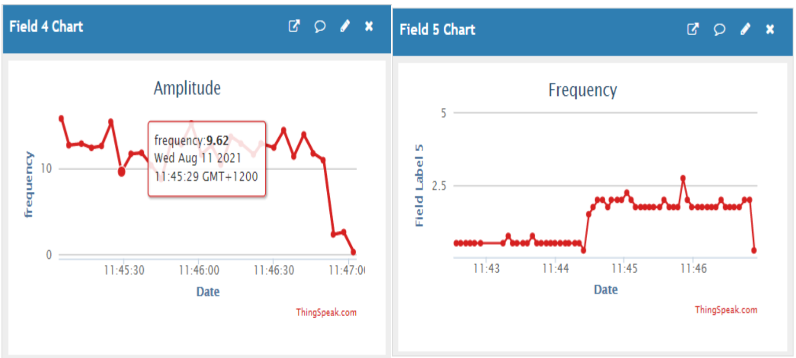
Figure 5.23. Cloud data packet format across fields 1 to 8

5.6 Design and implementation of mixed mode prehabilitation model

As discussed earlier, there are a number of key elements acting as a functional feature of the physical activities within the prehabilitation programme, such as intensity, exercise duration, and repetition of the activity. Daily living auxiliary factors also influence the prehabilitation outcome. Impact of the various activities is expressed in terms of mathematical equations (equations 1–4 section4.3.1 of Chapter 4) reflecting the processing of timely assessing the overall performance of the programme.

The main acting factor in the mixed mode prehabilitation model is the physical activities performed by the patient. Accordingly, the main research involvement of this study is how to recognise the different forms of the physical exercise, their associated intensities, the exercise duration, frequency of daily implementation, possible discontinuities (bed rest) for number of days, work out the total accumulated credit gained, and active time daily and weekly leading to the overall programme progress assessments.

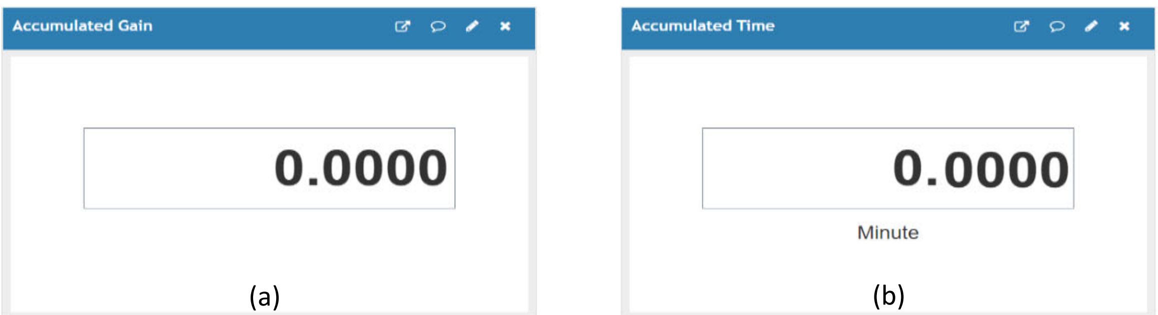
The procedure that was followed included the healthcare professionals requesting patients to perform some physical activities (within the nine types indicated in section 5.3.1) under supervision with the different intensities. Furthermore, the WSD was attached to the patient's ankle to collect, process, and send the data to the IoT cloud through the Internet gateway for visualisation and further processing. A long-term data repository was formulated at a local or remote database. The data were stored in both the gateway and the IoT cloud as a reference for the system record and are related to the same sensor ID user. Figure 5.24 illustrates sample data collection of the base data of dominant spectrum and the associated acceleration amplitude.

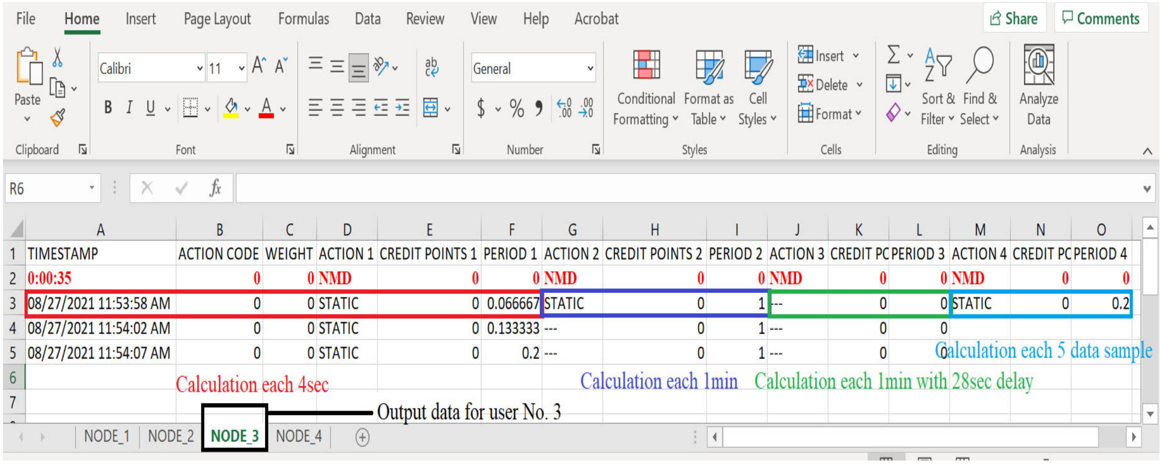


Activity	Weight	Frequency	Amplitude	Intensity
WL	0.33	1.25	7-10	0.75
WM	0.33	1.75	20-26	1
WV	0.33	1.75	16-30	2
TML	0.33	1.25	7-10	0.75
TMM	0.33	1.5	12-18	1
MV	0.33	1.75	16-30	2
CL	0.33	0.75	12-18	0.75
CM	0.33	1.25	24-40	2
CV	0.33	1.5	45-60	2
CTL	0.4	0.75	7-11	1
CTM	0.4	1	18-26	1.5
CTV	0.4	1.25	24-30	2
ROL	0.4	0.25	19-42	2
ROL	0.4	0.5	3-8	1
ROM	0.4	0.5	8-21	1.5

Figure 5.24. Showing the data collected from the WSD

In the next stage, when the patient started performing the prescribed physical activity remotely, the remote monitoring system started capturing and analysing the received data in accordance with the boundary rules discussed in Section 4.2. As part of the mixed mode prehabilitation programme, healthcare staff remotely monitored the patient's activities in accordance with the prescribed exercises. In an extreme case, such as no action for a whole week or daily extra gain credit exceeding the setup threshold, the system alarmed both the patient and medical staff. Depending on the patient’s situation and other factors, such as surgery schedule, the prehabilitation period could vary from two to eight weeks. As an example of calculations for the different prescribed physical activities, the four-week prehabilitation scenario for the patient performing remotely the mixed mode prehabilitation model is considered. An average accumulated gain of 20 points is required at the end of the programme, and a minimum time of 150 minutes per week with moderate intensity or equivalent, while a minimum of 10 minutes were required for each session at moderate intensity. After every 24 hours, the monitoring produced a new output file starting at zero for the accumulated time and gain. Figures 5.25 a and b depict both output result and system counter.

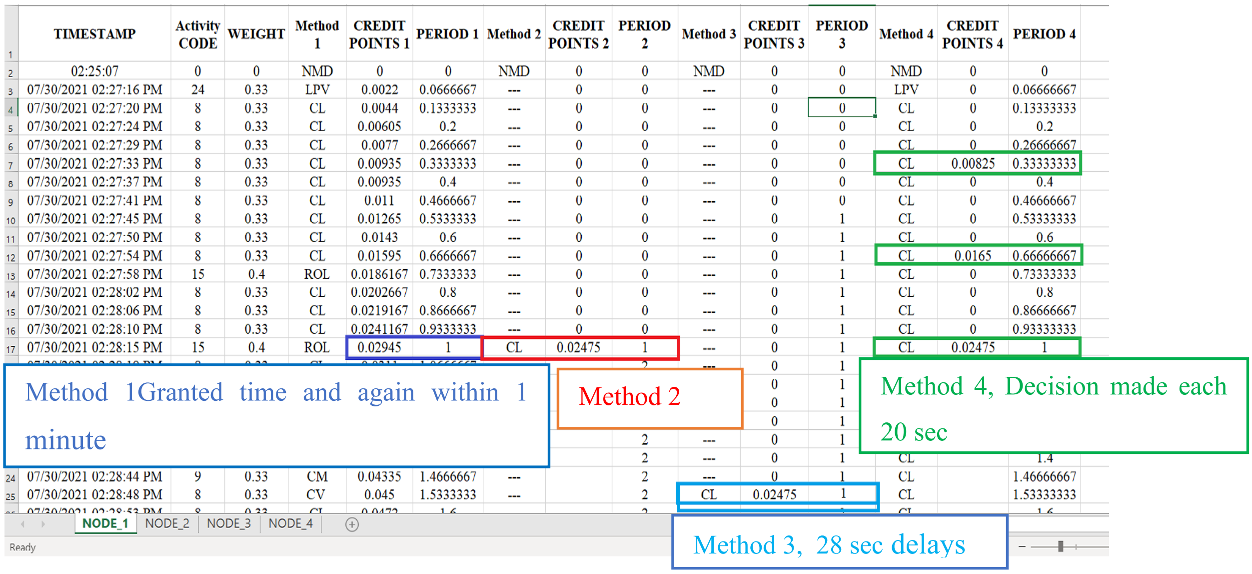




	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	TIMESTAMP	ACTION CODE	WEIGHT	ACTION 1	CREDIT POINTS 1	PERIOD 1	ACTION 2	CREDIT POINTS 2	PERIOD 2	ACTION 3	CREDIT PC	PERIOD 3	ACTION 4	CREDIT PC	PERIOD 4
2	0:00:35	0	0	NMD	0	0	NMD	0	0	NMD	0	0	NMD	0	0
3	08/27/2021 11:53:58 AM	0	0	STATIC	0	0.066667	STATIC	0	1	---	0	0	STATIC	0	0.2
4	08/27/2021 11:54:02 AM	0	0	STATIC	0	0.133333	---	0	1	---	0	0			
5	08/27/2021 11:54:07 AM	0	0	STATIC	0	0.2	---	0	1	---	0	0			

Figures 5.25.a and **b** Start-up system calculation on both gateway and TS.

As a result, the accumulated time and gain for every physical activity were recognised and calculated by comparing the sensor data with the stored database and then the four calculation methods were applied to each incoming data input as discussed before. Static and any unrecognised activity across all four methods was given zero gain credit. Real-time activity recognition, accumulated time, and gain credit were stored in the CSV file (see Figure 5.26).



	TIMESTAMP	Activity CODE	WEIGHT	Method 1	CREDIT POINTS 1	PERIOD 1	Method 2	CREDIT POINTS 2	PERIOD 2	Method 3	CREDIT POINTS 3	PERIOD 3	Method 4	CREDIT POINTS 4	PERIOD 4
2	02:25:07	0	0	NMD	0	0	NMD	0	0	NMD	0	0	NMD	0	0
3	07/30/2021 02:27:16 PM	24	0.33	LPV	0.0022	0.0666667	---	0	0	---	0	0	LPV	0	0.06666667
4	07/30/2021 02:27:20 PM	8	0.33	CL	0.0044	0.1333333	---	0	0	---	0	0	CL	0	0.13333333
5	07/30/2021 02:27:24 PM	8	0.33	CL	0.00605	0.2	---	0	0	---	0	0	CL	0	0.2
6	07/30/2021 02:27:29 PM	8	0.33	CL	0.0077	0.2666667	---	0	0	---	0	0	CL	0	0.26666667
7	07/30/2021 02:27:33 PM	8	0.33	CL	0.00935	0.3333333	---	0	0	---	0	0	CL	0.00825	0.33333333
8	07/30/2021 02:27:37 PM	8	0.33	CL	0.00935	0.4	---	0	0	---	0	0	CL	0	0.4
9	07/30/2021 02:27:41 PM	8	0.33	CL	0.011	0.4666667	---	0	0	---	0	0	CL	0	0.46666667
10	07/30/2021 02:27:45 PM	8	0.33	CL	0.01265	0.5333333	---	0	0	---	0	1	CL	0	0.53333333
11	07/30/2021 02:27:50 PM	8	0.33	CL	0.0143	0.6	---	0	0	---	0	1	CL	0	0.6
12	07/30/2021 02:27:54 PM	8	0.33	CL	0.01595	0.6666667	---	0	0	---	0	1	CL	0.0165	0.66666667
13	07/30/2021 02:27:58 PM	15	0.4	ROL	0.0186167	0.7333333	---	0	0	---	0	1	CL	0	0.73333333
14	07/30/2021 02:28:02 PM	8	0.33	CL	0.0202667	0.8	---	0	0	---	0	1	CL	0	0.8
15	07/30/2021 02:28:06 PM	8	0.33	CL	0.0219167	0.8666667	---	0	0	---	0	1	CL	0	0.86666667
16	07/30/2021 02:28:10 PM	8	0.33	CL	0.0241167	0.9333333	---	0	0	---	0	1	CL	0	0.93333333
17	07/30/2021 02:28:15 PM	15	0.4	ROL	0.02945	1	CL	0.02475	1	---	0	1	CL	0.02475	1
24	07/30/2021 02:28:44 PM	9	0.33	CM	0.04335	1.4666667	---		2	---	0	1	CL		1.46666667
25	07/30/2021 02:28:48 PM	8	0.33	CV	0.045	1.5333333	---		2	CL	0.02475	1	CL		1.53333333

Figure 5.26. Four methods for activity recognition with accumulated time and gain credit.

The above procedure was repeated whenever WSD started working. The system summarised the physical activity with accumulated time and gain on a daily and weekly basis. In addition, when there was no activity within certain days or the credit of the physical activity was much lower than the target gain, a warning message was sent to both healthcare staff and patient, as well, with the different form of details.

The expected granted gain versus ideal gain within a four-week prehabilitation programme and accumulated gain versus time of each physical activity are presented in Figures 5.27 and 5.28, respectively.

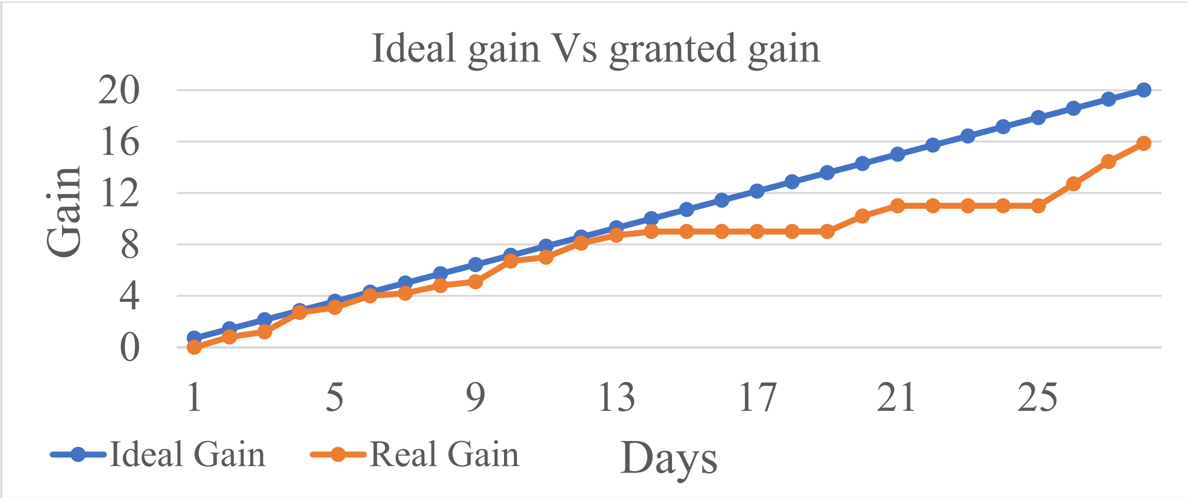


Figure 5.27. Granted gain versus number of days for four-week mixed-mode prehabilitation programme

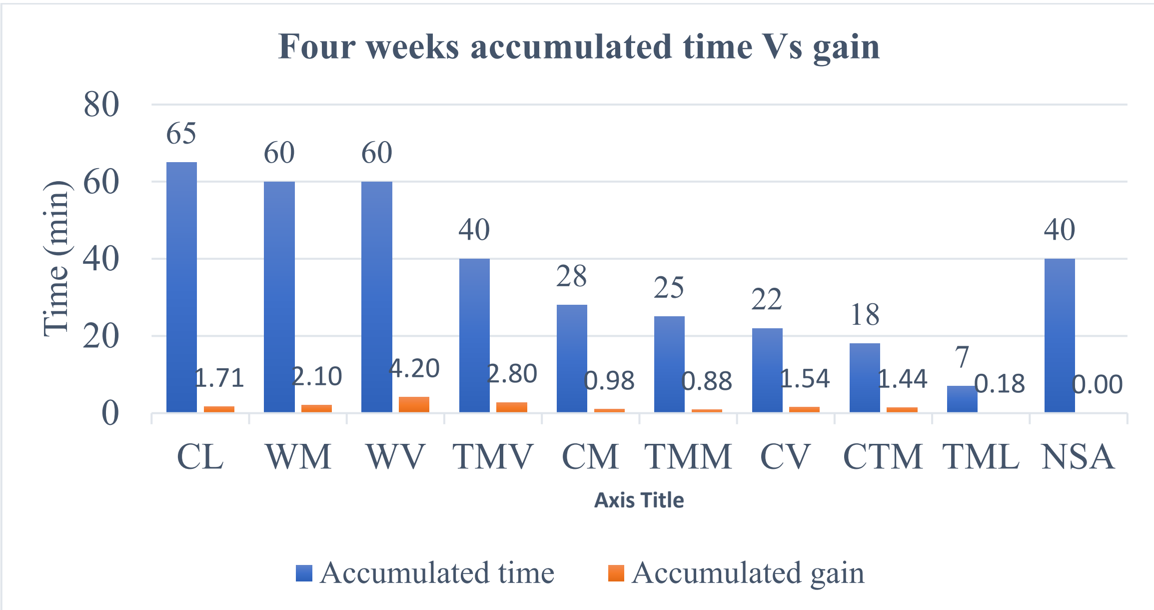


Figure 5.28. Accumulated time and gain of each physical activity within four-week prehabilitation programme

5.7 Summary

Different components of the Cyber Physical System have been analysed and tested for system performance and capability to support the mixed mode prehabilitation model, among other factors. The WSD was capable of handling the extracted data during different physical activities in terms of data storage (raw and processed), data processing (filtered data, calibration and FFT processes), data transmission bit rate and range to the upper level. Moreover, size, weight and power consumption were also designed and tested to verify user comfort. Significantly, WSD unprocessed data transmitted to the gateway showed a high rate of packet loss in comparison with the fully processed data (FFT data). The limitations of the gateway in dealing with multiple simultaneously received data from different WSDs have been overcome successfully. The gateway was capable of handling five WSDs at the same time while being capable of data analysis, data storage, data processing and transmitting results to the upper level without significant delay. Four activity recognition methods have been evaluated in different scenarios. M1 and M4 were found to be more suited to short-term activity recognition than M2 and M3. Buffer size and latency played a negative impact on activity recognition in M3. Accordingly, both buffer size and latency of buffer storing data may be reduced to enhance the activity recognition performance of M3. Additionally, high packet percentages of the packet loss and signal dropped were noted with more than six WSDs, with over a distance of 30 metres between the gateway and the WSD. TS was selected as an IoT cloud for visualisation, long-term data repository and further data analysis. The cloud demonstrated the ability to retrieve and visualise the various types of vital information received from the gateway.

Chapter 6 Results and Use Cases

6.0 Introduction:

This chapter introduces the Cyber-physical system performance and mixed mode prehabilitation programme assessment results based on real-life scenarios. Section 6.1 discusses the activity recognition challenges based on the individual's personalised and non-personalised database. This is followed by describing a case study scenario where a mixed mode prehabilitation programme is implemented in real-life circumstances in section 6.2. Section 6.3 discusses the Cyber-physical system in terms of packet loss, communication range, number of WSD, gateway data processing delay and ThingSpeak (TS) visualisation. Section 6.4 discusses the case scenario and 6.5 discusses a real-life 6MWT testing outcome over six-weeks prehabilitation programme.

6.1 Participants

Forty-three participants were involved in the study, which is approved by the Auckland University of Technology Ethics Committee (AUTEC reference number 19/212). The age of the involved individuals ranged from 20-91. However, for the purpose of this study, participants were divided into three age groups (young, middle-aged, and elderly) with most participants being above 65 years to represent demographics of people undergoing major abdominal surgery. A group of males and female participants with health conditions awaiting abdominal surgery also participated in the study (Table 6.1).

Over 60% of the participants did not complete the prehabilitation programme (four-six weeks). The shortest participation period was two sessions of 35- 60 minutes per week or over two weeks. Approximately 90% of participants performed the physical activities using AUT physiotherapy gymnasium while the other 10% of the participants were already involved in a special AUT exercise programme for people over 60, called "never2old" [168]. The prescribed physical activities during each session were performed under direct supervision. For the data processing and data transferring to the cloud, a standby base station gateway was installed at the gymnasium as previously described in Chapter 3. The initial session used a general-purpose database for all participants. This is followed by subsequent personal database that has been built up for each participant. Finally, additional outdoor sessions as well as home-based sessions were added to AUT gymnasium sessions for validation purpose. 12 % (i.e., 5) of the total participants were involved in these additional activities.

Table 6.1 Summary of participants in this study by age, gender, and health status.

Gender	Age range	Health condition	Participants No
Male	20-27	Young healthy	3
Male	48-57	Middle age healthy	3
Female	44-51	Middle age healthy	3
Male	65-91	Elderly healthy	11
Female	65-83	Elderly healthy	8
Male	65-81	Elderly abdominal health condition	9
Female	60-78	Elderly abdominal health condition	6

6.2 Activity Recognitions Challenges

Three distinct database types were subjected to the same four methods for movement outlier detection and correction. The first category is the personalised database (as discussed in Chapter 5, section 5.4.1), which contains training data taken from the same individual while engaging in various physical activities. Reference identifiers extracted from these training data were then used for the four methods of activity recognition. The second database type is based on multiple categories of participants into groups. Each group has a common database. At this stage the categorization has been based on the span of the FFT dominant frequency and associated acceleration ranges. This may in future work follow a given feature that may relate to age span, health condition, and/or others like physical feature. For example, activity recognition system recruits non-personalised database in the first physical activity session at starting prehabilitation program. Then by AI the system trains itself and the database is moved to categorised after the second physical session. Later on, the database being more mature to become personalised, this could happen without user interaction.

The third type of databases used is a general database (non-personalised) that covers all ages and conditions (previously discussed in chapter 5 subsections of 5.4), which was developed from physical activity information gathered from participants and patients. A common value for each physical activity was calculated from the group data and compiled in a shared (non-personalised) database and then utilised as a point of reference for new users when they begin undertaking various physical activities.

In the current study the four previously discussed methods (M1, M2, M3, and M4) were chosen for activity recognition using personalised, categorised, and non-personalised databases. Analysis was performed on four participants of each age group who conducted the same physical activities on the same pieces of fitness equipment three times in the same environments.

Figure 6.1 depicts the four participants (P1, P2, P3, and P4) conducting treadmill, cycling, rowing, and cross trainer at varied intensities on different days. In the initial session all participants performed the same four activities, and their performance data was stored in the system as a reference for each participant (personalised database). The precision percentages of the activity recognition for the same person ranged from 70% in TM to more than 95% in CL and CT activities.

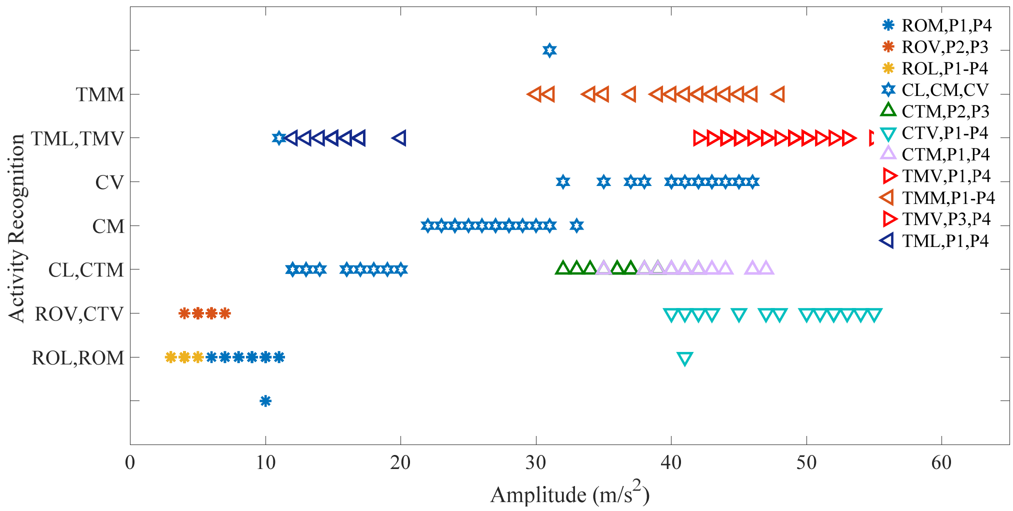


Figure 6.1 Personalised activity recognition from four participants performing the same activity at varying times.

The limited participant number (four participants in every four physical activities) means the categorised database has been created based on age group only, rather than fitness level. Accordingly, the categorised database was selected for participants aged 65 and above in this test. Therefore, the recognition percentages in the categorised database are showing less percentages in some activities such as treadmill and walking. The individual activity data (3-D frequency and amplitude) from accelerometer signals of the four participants were also compared to shared database (non-personalised data). Data was also analysed using the same methods from another four participants aged 48-73 years, who performed an additional four physical activities (walking, leg press, step up and staircase ascending / descending) at different exercise intensities. The outcomes of both groups for the eight physical activities can be seen in Table 6.2 and Figure 6.2. The table shows the comparison between activity recognition percentages in personalised, categorised and non-personalised database of eight different physical activities. The figure shows the slope of activity recognitions against different databases.

Table 6.2 The percentage of recognition of each activity for personalised, categorised, and non-personalised data.

Physical activity	Personalised (%)	Categorised (%)	Non-personalised (%)
Cycling	94	88.5	85
Cross Trainer	90.5	80.7	76
Rowing	90	84	81
Leg Press	90	81	78
Treadmill walking	82	69	67
Walking	73.5	58	56
Staircase	30-45%	28-38%	25-35%
Step Up	35-45%	31-41%	25-35%

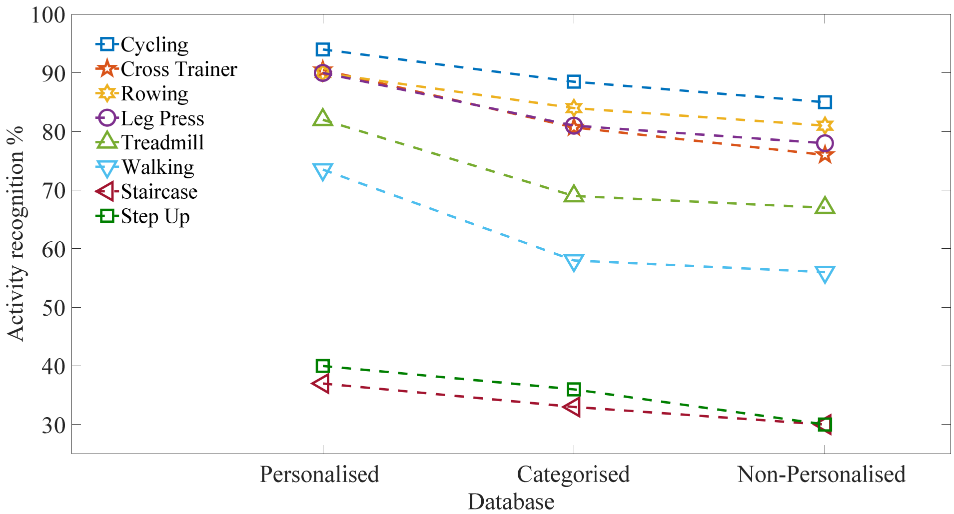


Figure 6.2 Shows the slop of eight activity recognitions based on different types of databases.

The physical activities illustrated in the above table can be divided into two groups. The first group represents those activities (cycling, cross trainer, rowing and leg press) where a high percentage of the activity recognition was evident when using both personalised and non-personalised databases (Table 6.2). The high level of recognition in this group of activities was because each activity had minimal overlap in amplitude and frequency measures and a fixed position (sitting on bike saddle). This group of activities were further classified into two categories based on the movement patterns associated with them. Cycling and cross-trainer are classified as the first category, where the participants were asked to perform the three levels of intensities based on cadence (velocity) measures of 50, 70, and 90 rpm, which represented light, moderate, and vigorous intensities respectively. Rowing and leg press are classified as the second category where the movement velocity was similar for each intensity level resulting in relatively stable accelerometery parameters (frequency and amplitude) across intensity levels. Accordingly, all four recognition methods achieved high recognition percentages for both cycling and cross-trainer. In contrast, there is a slight difference in the analysis of the second category (rowing and leg press). The movement range of the lower limbs is relatively small (around 1-metre), so the produced amplitude and corresponding frequency will be low. In addition, the repetition in the movement cadence will produce consistence in the extracted accelerometer components, as well.

The second group represented the physical activities with lowest percent of recognition and included staircase, step up, walking and treadmill walking. The lower percentage of recognition for these four activities could be due to having more overlap with other physical activities and whole human body movements with different cadence. Land-based and treadmill walking also showed low recognition rates, particularly when using the non-personalised recognition system. This is probably due to factors such as the individual and age-related differences in gait parameters (step rate and foot position at heel strike) that can influence accelerometery readings [169]. In addition, the participants did not necessarily walk with the same speed for a given intensity during the test which leads to variation in the output data that had a negative effect on the recognition percentages [169].

The other two physical activities with low recognition percentages (staircase and step up) present a clear example of inconsistency and overlapping. To understand the reason behind lower percentages of activity recognition, two minutes of staircase physical activity accelerometer extracted components (frequency and amplitude) have been selected for analysis using both personalised and non-personalised databases. The wide range of amplitude (3 to 35 m/s^2) and frequency (0.25 to 3.75 Hz) measures recorded during this activity increasing the chances of overlapping with other activities. Figure 6.3a shows accelerometery data analysis of staircase ascending/descending over a two-minute period performed by a 51-year-old male and a 57- and 67-year-old female at AUT physiotherapy gymnasium. Figure 6.3b demonstrates the amplitude and frequency of each participant. The amplitude range for the male was between 22-35 m/s^2 while the range of the amplitude for the other two female participants was mainly between 5-15 m/s^2. The frequency components of all participants were spread between 0.25 - 3.75Hz for the two minutes of physical activity.

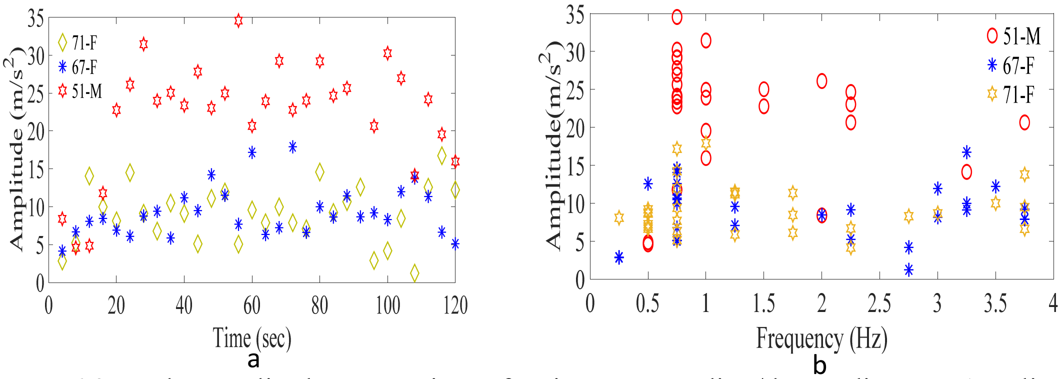


Figure 6.3 a. The amplitude versus time of staircase ascending/descending. **b.** Amplitude versus frequency for same activity and period.

Figure 6.3c. shows the same two minutes of activity recognitions using a personalised databased and the M1 recognition technique. This was used because of the inconsistency of the other methods which failed to accurately detect the actual activity. The M1 technique was able to recognize six different physical activities for 51-year-old male and the 67-year-old female, and eight different activities for the 71-year-old female. The percentages of occurrence of each activity are illustrated in table 6.3.

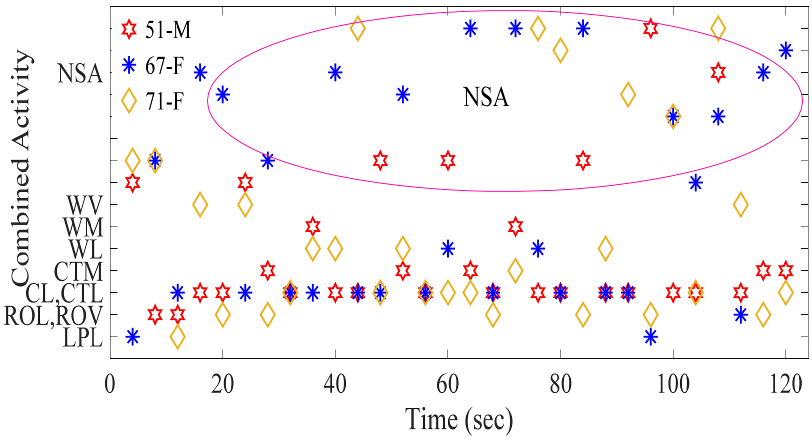


Figure 6.3 c. Two-minute analysis of staircase ascending/descending Combined activities Vs time

Table 6.3 The percentages of each combined activities of the participants (51-M, 67-F, and 71-F).

Activity combined in 2-minutes staircase (ascending/descending)	51-M	67-F	71-F
CL	7%	37%	23%
CTL	40%		
CTM	17%		3%

ROL	7%	3%	10%
ROV			10%
LPL		7%	3%
WL		7%	13%
WM	7%		
WV		10%	10%
TMM			
NSA	23%	36%	27%

The table above indicates that the staircase activity was identified as a variety of other physical activities. The staircase activity was identified as NSA in a large number of occurrences in all three participants (23%, 36% , and 27%). Figure 6.3 b. shows that the NSA data components are high frequency with a low amplitude (more than 5 m/s^2), and these value features did not occur with other activities. Hence, the NSA values do not correspond to any physical activity listed in the personalised database. As a result of the preceding discussion, M1 determined the value of NSA as a staircase activity; and hence, the staircase activity recognition percentages will be based on the NSA percentages. This gives an indication of the reason behind low recognition percentages in the staircase and step-up activity. This option may be preferable at this level to forfeiting the entire gain and time associated with this activity.

6.2.1 Short Term Activity Recognition

This section will present the challenges of short term (1-minute) activity recognition based on different logical methods. Both personalised and non-personalised (shared data) were tested to present the percentages of activity recognition from data collected while each participant was performing different physical activities at varying intensities.

Data was collected from 23 participants aged from 20 to 81 years through logical activity recognition methods (M1, M2, M3, and M4) previously discussed in Chapter 5. Figures 5.4 and 5.5 show the six different activities (CL, CM, CV, TMV, LP, Rest) that went through different logical activity recognition methods using personalised and non-personalised database analysis. Figure 6.4 shows eight minutes of physical activity where each activity occurs for one minute (60 sec). The activity sequences were Rest, CL, CM, CV, Rest, TMV, Rest, and LP. Rest activity had an amplitude of less than 1m/s^2 with irregularity in the dominant frequency, and hence the credit gain for across all logical methods was zero.

Figure 6.4. shows the eight activities recognised via different methods using the personalised database. The direct method (M1) showed recognition percentages of 86%, 93%,93% and 86% for

CL, CM, CV, and LPL, respectively, when using the personalised database. M2 had a recognition of 100% for the same four physical activities. M3 was not used for data recognition analysis of these activities due to the test period of each activity being relatively short (one minute) and the buffer of the M3 starting after 27sec of M2. This would mean that the buffer used in M3 would store half readings of two adjacent activities, resulting in significant overlap of activities and low data consistency. As discussed in chapter 4, M4 used five readings with different techniques. This method firstly makes separate 20 second buffers of data (five readings). The live data stream is stored in the main buffer and the rectified buffer keeps the rectified data. This technique identified the first five readings as LPL, LPV, CL, CL, CL, and then LPL and LPV were identified as CL via analysis of the rectified data. This resulted in 100% recognition for the CL, CM, CV, and LPL giving a full credit gain. TMV was unable to be recognised using M2 because data consistency (73%) was less than the threshold level 80%. This resulted in the whole minute gain being equal to zero. Nevertheless, M4 successfully recognised 100% of TMV and a credit gain was achieved. In summary, when using the personalised database, the mean recognition percentages using the M1, M2 and M4 for the five minutes physical activity (CL, CM, CV, TMV, and LPL) were 86%, 80%, and 100%, respectively.

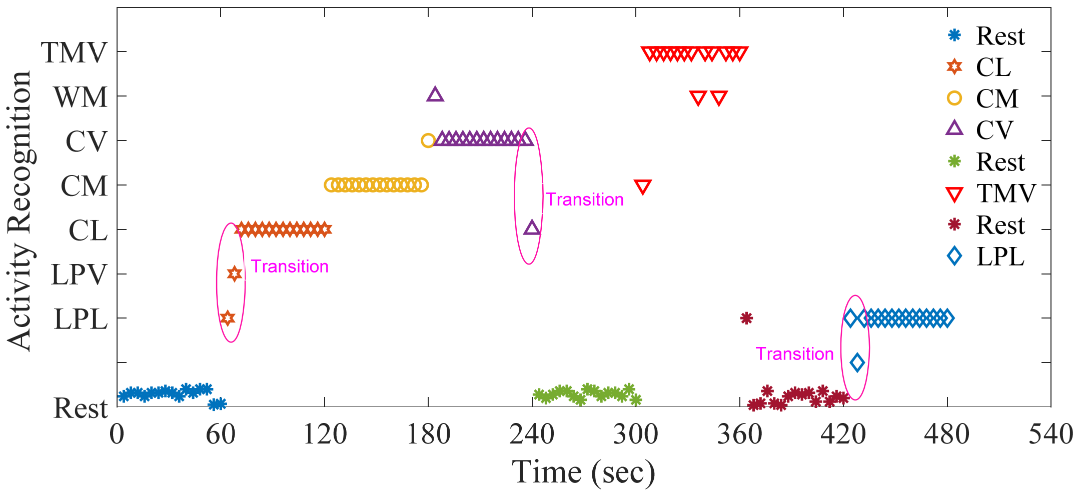


Figure 6.4. Eight physical activities with different intensities using the personalised database.

A similar analysis was performed on the same raw activity data using non-personalised database (Figure 6.4). Some activities can be easily distinguished from others by either the dominant frequency content or the amplitude related to the intensity of that dominant frequency. As a result, one pair of data collected during the specific physical activity may be identical to customised data, while the other pair may be outside of the range, leading to misrecognition of some physical activities. After gathering data from a variety of participants and patients (43 tests) over the project period of the research, the majority of differences in amplitude values among the subject data was discovered. In this test, to make tracking easier, the non-personalised database based on (amplitude data) was displayed in this figure as a reference rather than the frequency. In addition, to avoid the graph congestion the rest time between activities was omitted, which was present in the real scenario.

Figure 6.5 shows five different physical activities (TMV, LPL, CL, CM, and CV). M1 resulted in recognition percentages of 80%, 86% 93%, and 86% for CL, CM, CV, and LPL respectively. M2 and M4 attained 100% activity recognition for the same physical activities. Nevertheless, all methods failed to recognize TMV because the subject amplitude results did not match with reference data range. Due to the overlapping , M1 recognized the TMV as WL. In this case the impact of incorrectly identifying light walking (I =0.75) instead of treadmill walking at a vigorous intensity (I =2) resulted in a substantial underestimation of credit gain.

In summary, the total recognition percentages of the M1 and other logical methods for five different activities using the non-personalised database were 69% and 80%, respectively. This would indicate that the personalised database had much higher recognition percentages than the non-personalised database.

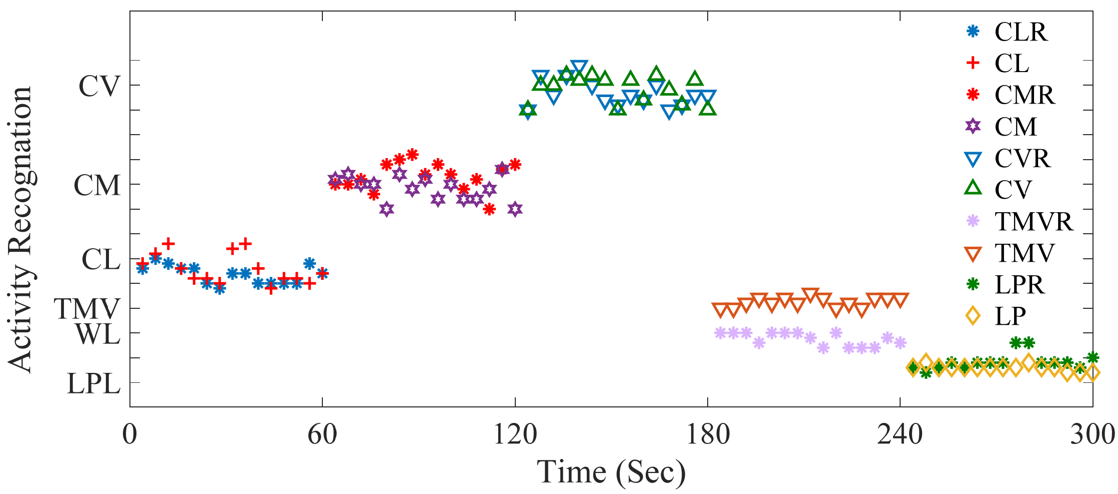
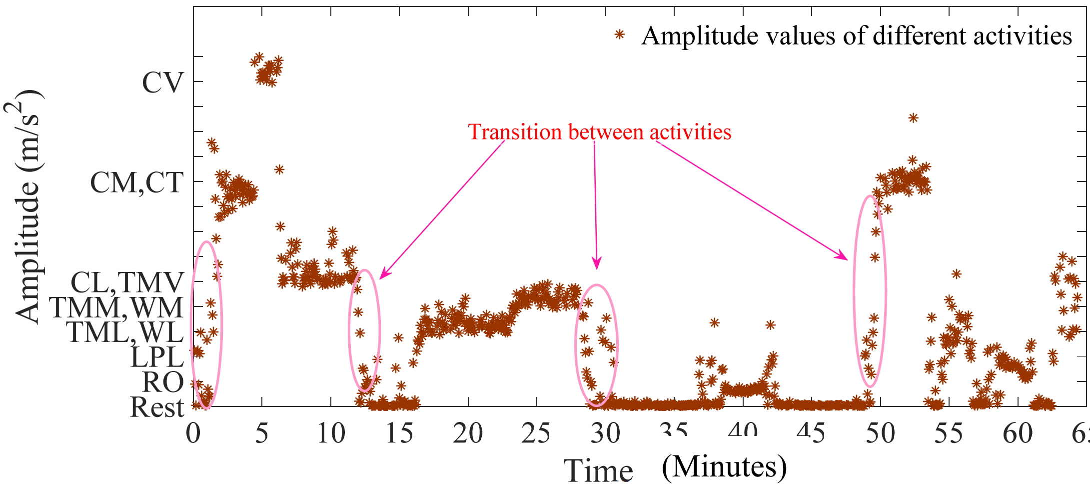


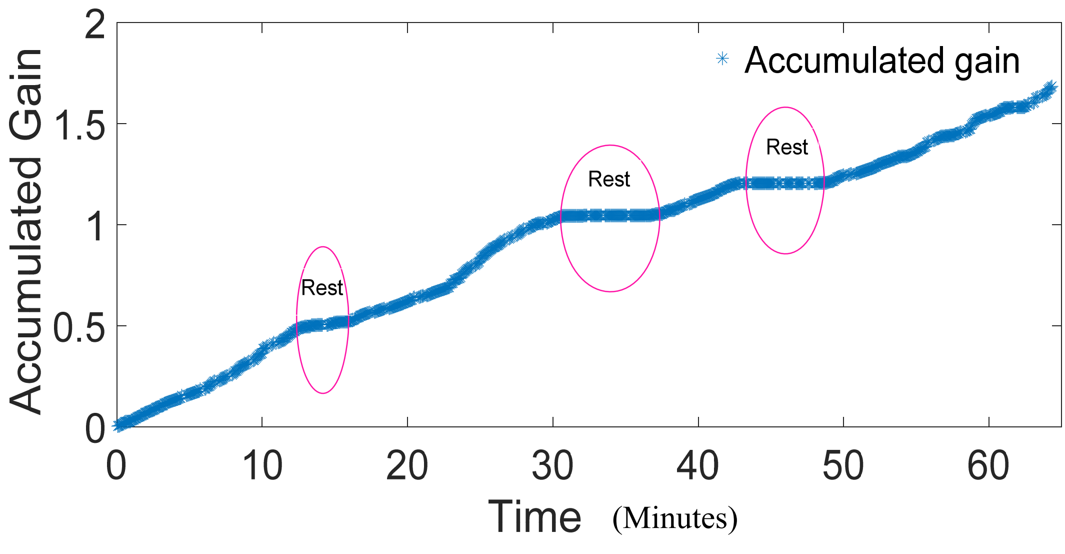
Figure 6.5. Recognition of the five physical activities based on non-personalised database. “R” in the legend refer to reference value.

6.2.2 Long-Term Activity Recognition

This section discusses the long-term activity recognition and accumulated gain and time for a 65-minute physical exercise session at AUT physiotherapy gymnasium under direct supervision. Figure 6.6 a show the 65-minute session of different physical activities for a healthy elderly female participant (71 years). The activities were performed in the following order: CM, CV, CL, Rest, TML, TMM, TMV, Rest, RO, Rest, CT, Rest, LP, and WL. The spectrum showed that some physical activities were in the same frequency range, which could lead to activity misrecognition and alter the accumulated gain. Figure 6.6 b shows that the accumulated gain value for the combined physical activities within the 65-minute session was 1.645, while the ideal gain should have been 1.85. The error value between ideal and actual result was 0.205, resulting in an accuracy percentage of 89% for the fourteen different physical activities performed at different intensities. The percentage of the missing gain was 11% meaning that around 6.5 minutes of actual moderate physical activity had not been recognised. This will be an acceptable result for the long-term physical activity, as these periods of misrecognition tended to be when the participant was transitioning from one activity to another, as illustrated in Figure 6a.



a



b

Figure 6.6. a. The amplitude measures for recognition of different physical activities throughout a 65-minute supervised exercise session and **b.** the accumulated gain for the activities.

6.3 Mixed Mode Prehabilitation Programme Case series

As discussed earlier in this chapter, forty-three participants aged between 20-91 years old participated in this research. Participants had a variety of activity levels, and some (n=17) had health conditions (abdominal cancer patients). Due to many obstacles related to a geographical area and patient health status, only 17 people completed the typical time period (four to six weeks) for the prehabilitation programme. The remaining participants performed the intervention activities over a period of one to three weeks. Participants were categorised into two groups. The first group consisted of healthy young and elderly participants, while the second group were elderly abdominal cancer patients.

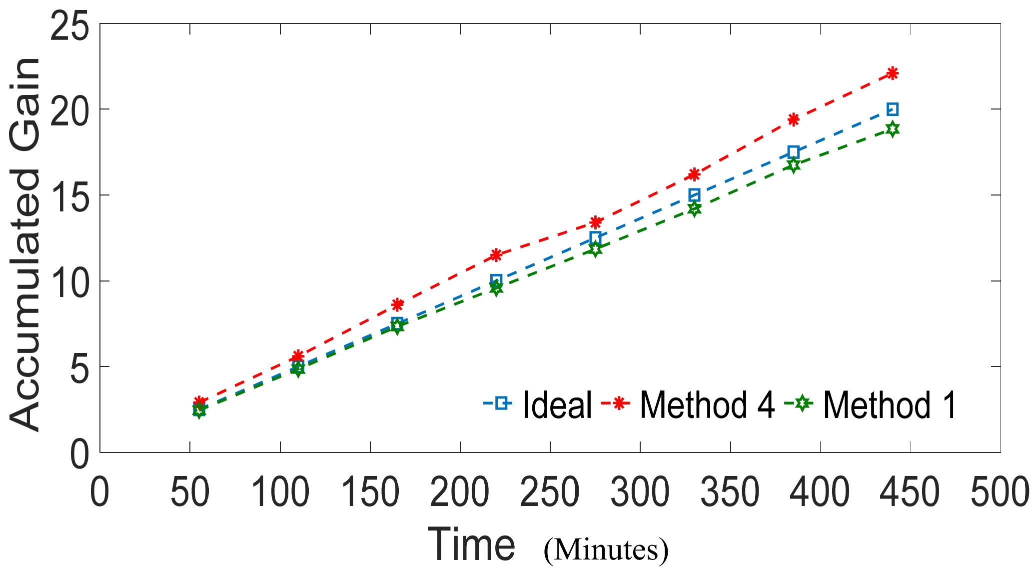
Both groups performed their exercise intervention at the AUT physiotherapy gymnasium. Participants joined the program at varying dates based on their availability, timetable, and referral date from the hospital. Participants attended exercise sessions two to four times per week. Table 6.4 illustrates the number of participants, physical exercises, and intensity of each group. Each exercise session was supervised by a researcher and a physiotherapist and lasted between 35-55 minutes.

Table 6.4. Participant numbers and group description, and the type and intensity of the physical activities undertaken at the gymnasium.

Health condition	Physical exercises	Intensity	Participants
Young and middle age healthy fit	cycling, treadmill, rowing, leg press, cross trainer, and walking	M, V	3
Elderly healthy fit	cycling, treadmill, rowing, leg press, and walking	M, V	6
Elderly healthy unfit	cycling, treadmill, rowing, and walking	L, M, V	4
Elderly abdominal health condition	cycling, treadmill, rowing, leg press, and walking	L, M, V	4

The direct supervision ensured that the participants/patients performed the physical activity as prescribed and enabled a comparison between the system activity recognition and performed physical activity for validation purposes. The four-week prehabilitation programme was selected instead of six-weeks to ensure that all participants/patients had the same time frame. The setting for the ideal target gain for every participant/patient was 20 points for the four-week programme. There was no substantial difference among the first three recognition logical methods compared with M4, so only M1 and M4 were selected for comparisons with the idle target gain. Furthermore, for the equity purposes, only 110 minutes per week (two 55-minute sessions) of physical activities performed at various intensities were considered for the analysis. Data from two sessions per week were selected because most participants attended two sessions per week and two separate sessions of data provided more clarity for graphing results. Therefore, each subject performed 440 minutes of physical activities at varying intensities for a four-week prehabilitation programme. This equated to a total gain of 20 points throughout the four weeks. The reason for setting the 20 points gain credit target for all participants was because these 20 points equated to weekly exercise recommendations for improving fitness, and secondly to validate if the target was feasible for healthy individuals and participants who had abdominal cancer with relatively low levels of fitness.

Figures 6.7 a, and b depict the accumulated time and gain of fit young and elderly healthy participants, respectively. The young and older healthy participants were able to perform physical activities at high intensities and achieve a high credit gain of 90-115% relative to the ideal target gain. However, the second group of cancer patients were only able to achieve between 65 and 85% of the target gain. The main reason for missing the 20-point credit target were because this group of participants were not able to achieve the specific intensity of the activity due to fitness issues.



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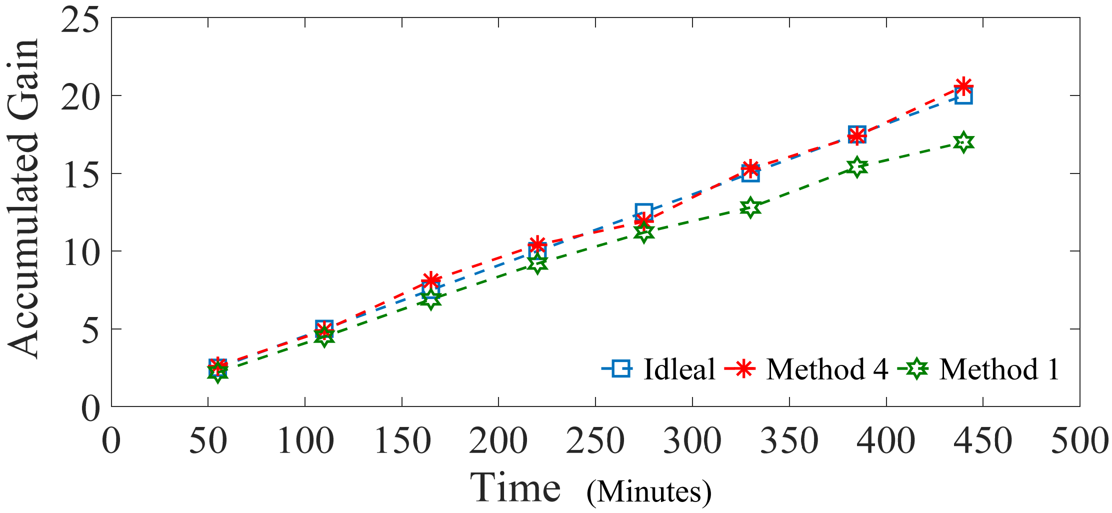
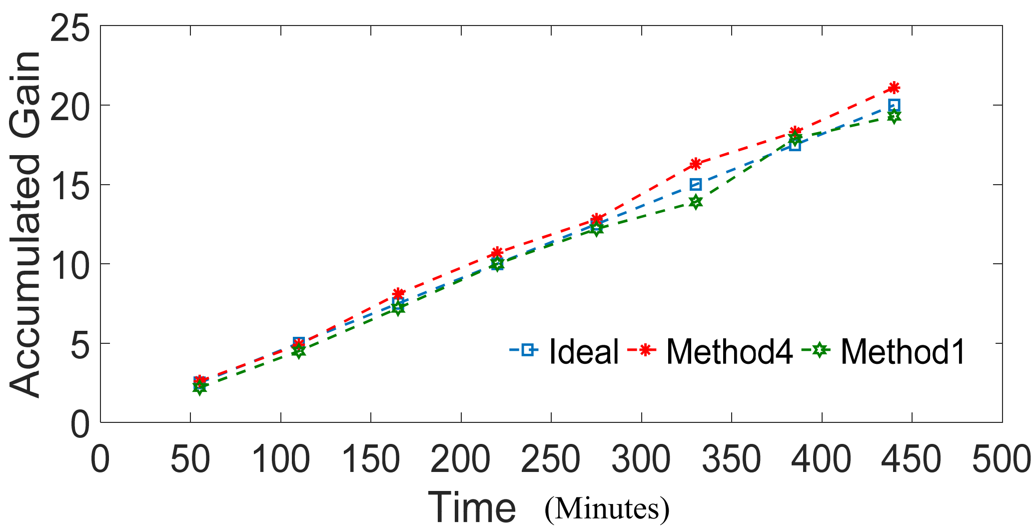


b

Figure 6.7. Accumulated gain versus time for **a.** healthy young and **b.** healthy elderly participants.

Figure 6.8 a and b demonstrate an example of four weeks of prehabilitation exercises for a healthy elderly participant and an abdominal cancer patient who was classified as having poor aerobic fitness via cardiopulmonary exercise testing. Figure 6.8 a. indicated that the healthy elderly patient who performed a four-week prehabilitation programme and had an accumulated gain of 105% based on M4 and slightly less than 100% of the target gain when using M1 calculations. In contrast, the elderly unfit abdominal cancer patient was unable to reach the 20-point target gain and only achieve 65% to 77% of the ideal gain. This would indicate that programmes, and the associated points gain, may have to be tailored for patients who have different levels of health and fitness. It would seem that healthy participants were better conditioned to cope with higher intensity activity than the cancer patients. Therefore, some adjustment would be needed to make by the physiotherapist or clinician for the patients with low fitness levels.



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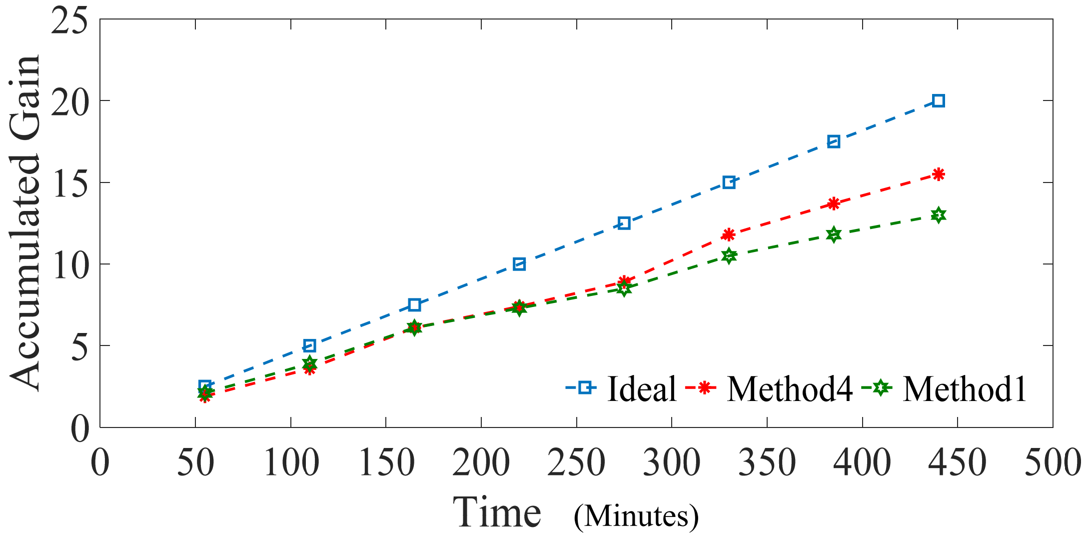


b

Figure 6.8. Accumulated time and gain of **a.** a fit elderly patient and **b.** an unfit elderly patient.

6.4 Cyber-Physical System Performance

This section provides an analysis of the performance of the different Cyber-physical system components used to manage a mixed mode prehabilitation programme. It will cover the performance of single and multi-users in terms of packet loss, time consumption of data analysis. It will also explain the gateway approach and the possibility of packet drop caused by the gateway becoming overwhelmed with more than one sensor or there is loss of data due to distance from the gateway, and how this affects latency in the cloud. The Cyber-physical system was subjected to different testing methods to reveal the system limitations and whether the system could cope with mixed mode prehabilitation programmes under different scenarios.

6.4.1 Path Loss Calculation

Packet loss of the data being received from the sensor was tested under different conditions, depending on the specifications of the transceivers (nrf24l01)[170], which include the WSD and gateway. The transmitted power was 0 dBm at 250 kbps, while the receiver sensitivity was -94 dBm at 250 kbps data rate. The gain of the microstrip antenna is 2 dBm, and it was connected to both transceivers in the WSD and the gateway. Based on the equation (1), shown below [171], the 1 m free space loss (FSL) was 40 dBm at 2.4GHz.

$$\text{FSL}=-20log_{10}(\lambda/4\pi R)\text{-------------------------------}(6.1)$$

Where, λ is the wavelength, and R is the distance between receiver and transmitter.

Accordingly, the received signal strength on gateway frontend can be determined by equation (2).

$$Pr(dB)=Pt(dB)+Gt(dB)+Gr(dB)-FSL(dB)\text{---------------}(6.2)$$

Where P_r is receiver power in dB, P_t is transmitter power in dB, Transmitter antenna gain (G_t), and Receiver antenna gain (G_r) [171].

Accordingly, P_r value for 1m distance between Tx/Rx will be as below:

$$Pr(dB)=0 +2+2-40 = -36 \text{ dBm}$$

Pr (-36 dBm) was considerably higher than the required -94 dBm (receiver sensitivity) for communication at the 250kbps data rate and hypothetically the link should work fine. Figure 6.6 shows two scenarios. The first is when the WSD is in line of site (LOS) with the gateway, and the second when the user is performing the physical activities in indoor environments where the walls and doors have an impact on the prorogation of the received signal.

Figure 6.9 shows the theoretical calculation of the maximum distance between WSD and gateway for both free LOS and indoor environments to maintain the communication link. The curves reflect the ideal communication link without considering the Tx/Rx antenna locations, Rx antenna height, and echo propagation, all of which could affect the communication channel link and reduce secured (Tx/Rx) distance substantially.

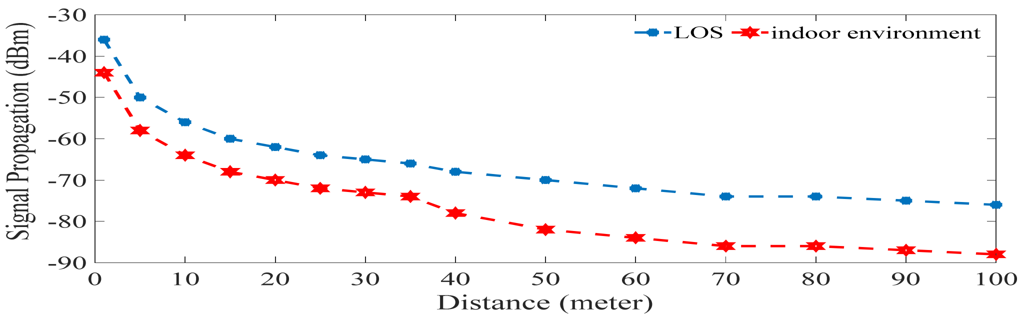


Figure 6.9. The relationship between signal propagation and distance for LOS and indoor environment.

Figure 6.10 shows the RPi3B and five WSD located at varied distances (5-25 m) from the RPi3B. The percentages of the packet loss were calculated as follows:

Packet loss = ((packet transmitted – packet received)/packet transmitted)) *100.

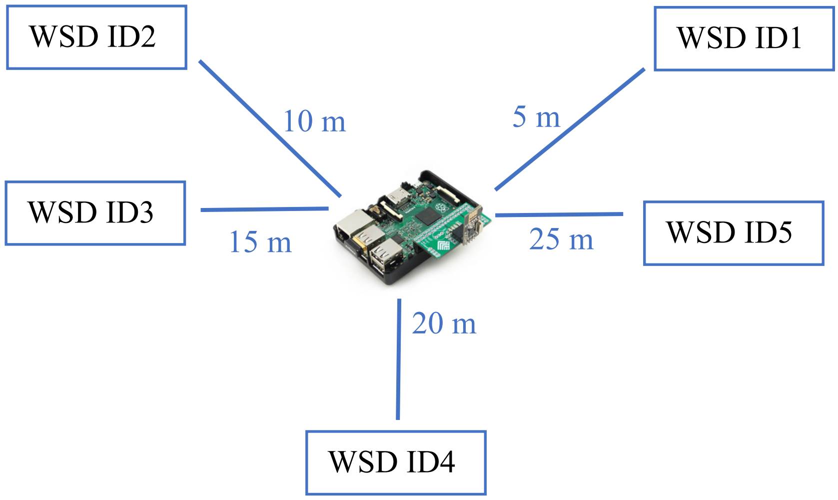


Figure 6.10. The Gateway with multi-WSD and different distances.

The two proposed schemes were used for the packet loss procedure. The first scheme used the single and multi WSD in free space LOS at varied distances from the RPi3B and the second scheme used single and multi WSD in an indoor environment (Figures 6.11 and 6.12). Figure 6.8 depicts the five-minute packet lost percentages tested for five WSDs added to the system progressively with the sensors in LOS of the RPi3B. A WSD was added each minute, then the packet loss is determined after each minute. These steps were then repeated with varying distances (5 m- 25 m) from the RPi3B. When the RPi3B was in LOS the addition of the first two WSDs to the system did not affect the packet loss. However, the system was affected when the fourth and fifth WSDs were added. This was particularly evident when distance between the WSD and gateway was increased. Thus, the communication link was compromised with the increase in distance and the associated increased packet loss.

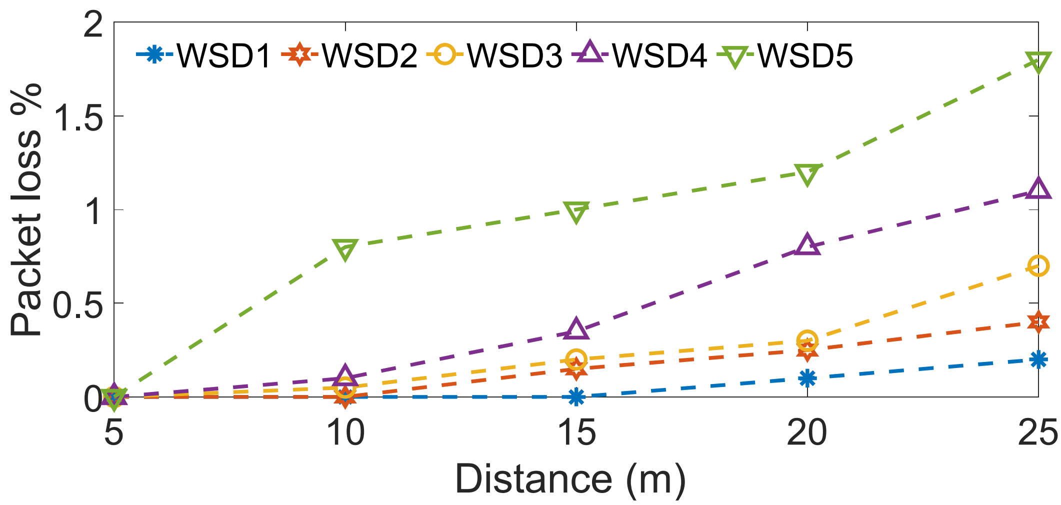


Figure 6.11. The percent of packet loss for multi-users and different distances LOS scenario.

The second scheme used the same methods as the first but was repeated in the indoor environment, taking into consideration the propagation presence of doors, windows, and walls. The percentages of packet loss increased promptly after a 15 m distance, specifically when the number of WSDs increased. Due to the indoor utilities, the channel link between WSD and RPi3B suffers from significant attenuation after 25 m which leads to increasing in the packet loss percentages, as well.

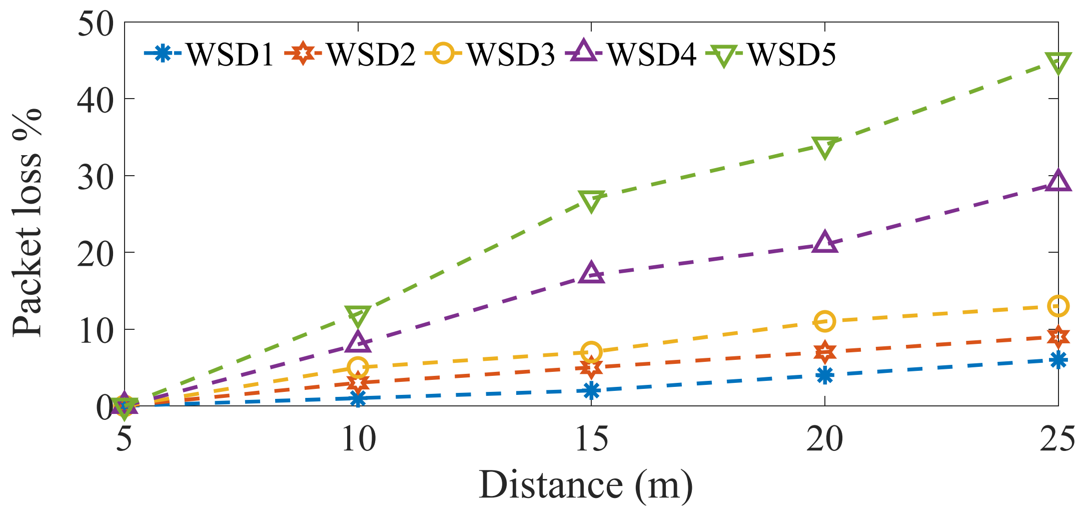
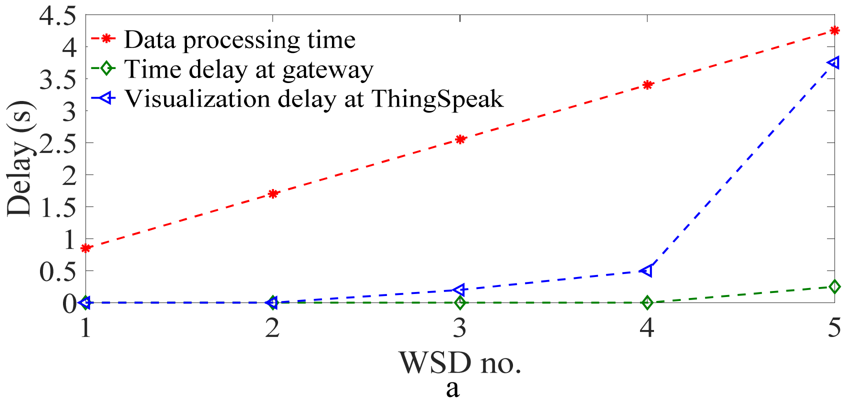
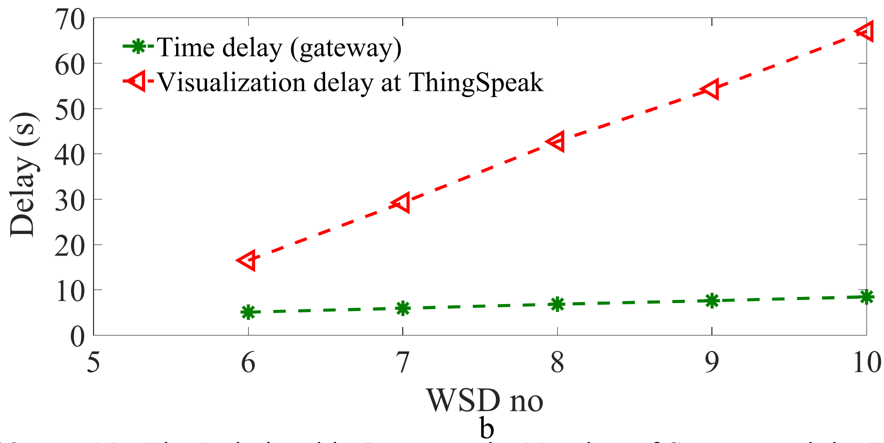


Figure 6.12. The percent of packet loss for multi-users and different distances based on the indoor environments.

6.4.2 Gateway and cloud latency related to the number of WSD

A linear relationship between the number of WSDs (Tx) and the execution time of incoming data at Rx (gateway side) was evident. The time of data processing at the gateway side for the single user (WSD) was about 0.86 seconds. The gateway needed approximately double this time to handle two WSDs, as the time frame between each incoming data from Tx was about four seconds. Therefore, the maximum number of WSDs processed by the gateway without delay was five devices. Figures 6.13a and b show the relationship between the number of sensors and the execution time at the gateway with accumulated visualisation delay in the TS for one minute. The one-minute cumulative time visualisation delay at TS for five WSDs was 3.75 sec which equated to a 255 sec (3.75 min) delay over one hour. The delay in both gateway and TS increases substantially when the number of WSD exceeds seven units collecting data at same time (Figure 6.13 b). However, the gateway could handle less than six WSD simultaneously without significant delay. Table 6.5 depicts the maximum WSDs that the RPi3B can process without delay and gives the cumulative time delays at TS. When the number of WSDs surpassed five, the cumulative delays were noticeable on the TS side (i.e., six WSDs handled by RPi3B required an extra 16.5 sec for one-minute of incoming data visualisation). In other words, one hour of data processing for six WSDs took additional 16.5 minutes to drive all data to the TS. As the mixed mode prehabilitation physical activity session did not exceed one hour, the RPi3B handled six WSDs simultaneously without significant visualisation issues. However, nine WSDs needed one additional hour to drive all the processed data to the TS. Thus, as depicted in Table 6.5, more than six WSDs could not be used simultaneously in this model.





Figures 6.13 a and b. The Relationship Between the Number of Sensors and the Execution Time at the Gateway and TS.

Table 6.5. Time delays at the gateway and cloud with respect to the number of WSD.

No. of WSD	Execution time (s) (gateway)	Output delay (s) (gateway)	One-minute TS visualisation delay (s)
1	0.85	0	0
2	1.7	0	0
3	2.55	0	0.05
4	3.4	0	0.95
5	4.25	0.25	3.75
6	5.1	1.1	16.5
7	5.95	1.95	29.25
8	6.85	2.85	42.75

9	7.62	3.62	54.3
10	8.47	4.47	67.05

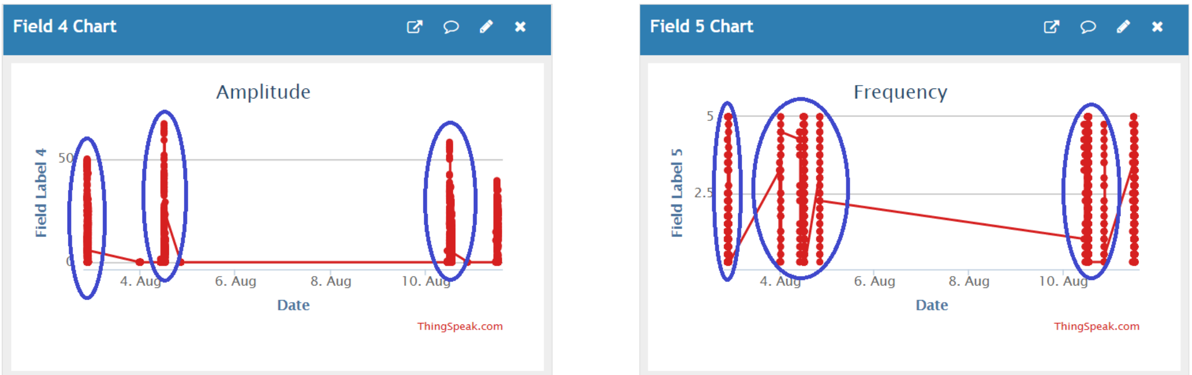
6.5 Mixed-Mode Prehabilitation Programme Practical Case

Three participants completed the mixed mode prehabilitation program: one elderly abdominal cancer patient waiting for the scheduled surgery and two middle-aged healthy people. The patients conducted three sessions within ten days (two sessions in the gym and one outdoor session), and the total accumulated time was approximately 140 minutes with varying intensity levels. The outdoor activity only involved walking with varying intensities. Nonetheless, the other two participants continued for two weeks, doing six sessions (three sessions per week, 100-130 minutes) as follows: three sessions of 45-60 minutes at the gym (cycling, treadmill, cross trainer, and rowing) with varying intensity levels, and three more sessions in outdoor environments (walking at varied intensities, and each session lasting between 30 and 45minutes). The portable RPiZW with WSD demonstrated in Figure 6.14 were given to all three participants and joined to the local Internet connection for the RPiZW. Specific TS channels were assigned to each participant, preventing data from being mixed up with other participants.

Figure 6.14. RPiZW, WSD, Strip Band, and USB Charger Cable.

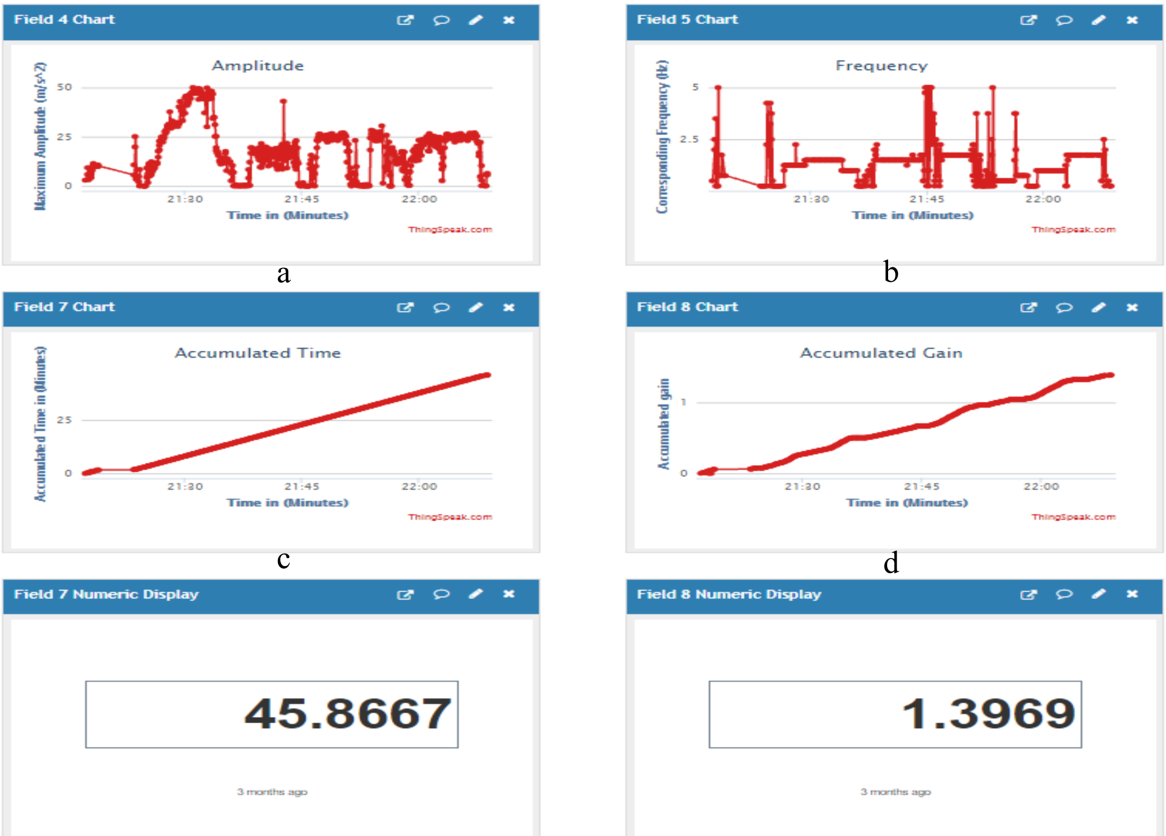
The preliminary data for the first and second participants were available during the first AUT physiotherapist lab session test, while the data for the third participant was not accessible.

Therefore, the personalised database was used for the first and second participants, whereas the shared database was a reference for the activity recognition for the third participant. Figures 6. 15 a and b indicate the TS visualisation of the three physical activity sessions in detail for the first participant. Figures 6.16a to d demonstrate more detailed data on one session conducted in the gym, illustrating the amplitude, frequency, accumulated time, and gain, while Figures 6.15e and f display the digital values of accumulated time and gain for the various physical activities in the same session.



a b

Figures 6.15. a. Amplitude and **b.** frequency for three sessions at different dates and time, respectively.



a b c d e f

Figure 6.16. a. amplitude, **b.** frequency, **c.** accumulated time, and **d.** accumulated gain credit with numeric displays of a single exercise session.

The above figures demonstrate that the system was able to attain data from the different activities, stored and analysed the offline data in the gateway and pushed the data to the cloud once the internet was reconnected again (for example, when the participant returned home). The system recognised that 82% of the actual activities that were performed in the gym, while this value was around 68% for outdoor activities (walking in varying intensities) due to the overlapping between walking and some other activities. The results were about the same for the second participant (83% at the gym and 65% recognition for outdoor walking). However, the results of the third participant with a shared database varied for different activities. For example, there was 95% recognition for the cycling, 78% for rowing and leg press and less than 65% recognition for the cross-trainer, walking and treadmill due to the overlapping between those activities. However, the missed recognition would not render the efforts unless the results of amplitude (A) and frequency (F) did not correspond to any database value. Therefore, the overlapping among physical activities would reduce the system performance from the point of activity recognitions; thus, the total efforts, including accumulated gain and time, would not be very effective.

Figure 6.17 indicates the mixed mode prehabilitation program results for the three participants. The percent of the ideal gain for the three participants were 78%, 72%, and 68%, respectively. These percent values show that the design and application of the IoT remote monitoring system supported a mixed mode prehabilitation program. Moreover, the target gain also doubled when the precise database fed the system, and the patient performed the prescribed physical activities.

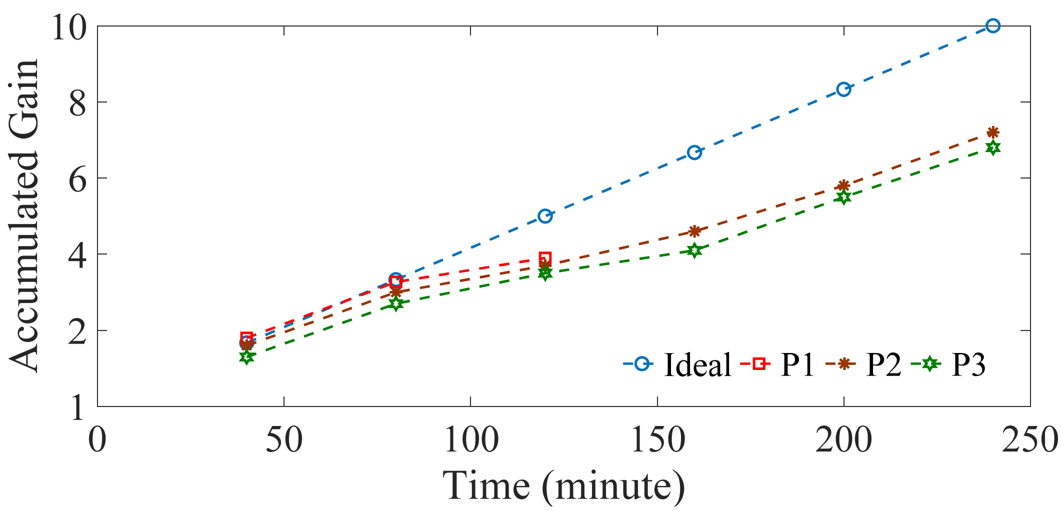


Figure 6.17 Accumulated gain for the three participants for a two-week mixed-mode prehabilitation programme. Note the blue line represents the ideal or prescibed credit gain.

6.6 Six-Week Prehabilitation Progress Results

As discussed in Chapter 2, a number of measures such as the distance walked in the 6MWT, Anaerobic Threshold (AT), and maximum oxygen uptake (VO2max) are used to assess progress. The 6MWT was selected as it was easier to apply in a clinical setting, better tolerated, and better-reflected activities of daily living than other walk tests.

More than 17 patients and participants with varying fitness levels participated in the prehabilitation program for (four to six weeks). Seven participants (three males and four females), of different age groups, were selected out of 17 available. As depicted in Figure 6.18, four participants showed improvements in 6MWT distances that exceeded the clinically meaningful 20 m needed to show an improvement in function over the six week intervention [43] (P2-P5). However, the other three participants (P1, P6, and P7) did not exceed the 20 m improvement threshold value, and their improvement in walking distance ranged from 2 to 3.5%.

The reason for this group (P2-P5) not attaining clinically significant improvements in 6MWT distance may have been due to previous low levels of engagement and initial “moderate” mobility based on exceeding an average 1m/s walking speed, and they failure to do regular physical activity[172]. It should also be noted that that the 6MWT distance is not an accurate measure of fitness compared to Cardiopulmonary Exercise Testing (CPET) and is less sensitive to changes in aerobic fitness. For the individuals who did improve 6MWT distance, they tended to show improvements in distance at about week four. By week four these participants were performing physical exercises between 30 and 45 minutes per session at a moderate to vigorous intensity three to five times a week. Therefore, the walking endurance / ability to walk level seemed improved substantially after week four. For example, for P1, who had an initial low mobility level of less than 1m/s [55, 172]walking speed and did not do any regular fitness activities prior to the prehabilitation intervention, the improvement was 3.5%. In contrast, both P6 and P7 had initial 6MWT velocities (1.25 and 1.35 m/s respectfully) that indicated a moderate level of initial fitness and were already engaged in physical regular exercise sessions at the gym and home. Thus, the six-week prehabilitation programme did not improve their 6MWT distance (1.5-2.5%).

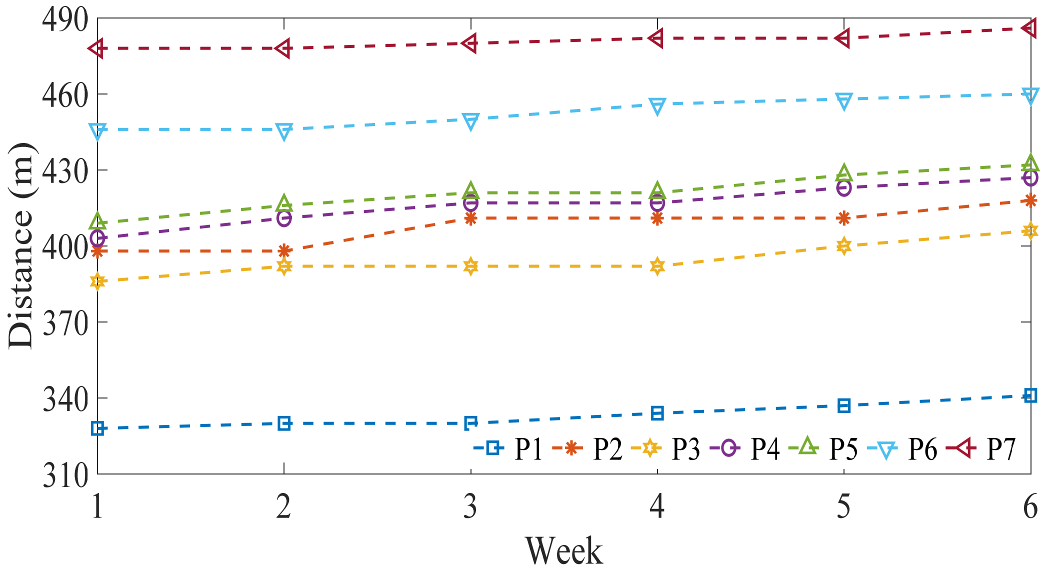


Figure 6.18 Seven Participants performing 6MWT assessment during six-week prehabilitation programme.

6.7 Summary

The suggested cyber-physical system is built on a three-level design that includes wearable sensors, Internet gateways, and cloud computing. The importance of edge computing at the wireless sensor to increase overall performance is reflected in the assessment of the system functionality at the three primary levels. Furthermore, the findings of the experiments show how personalisation and non-personalisation logical analysis of movement dynamics affect alignment with reality. For seven activities, the system was able to recognise more than 70% of personalisation data while the percentages were considerably less (55%) for non-personalisation data. This highlights the importance of establishing a personalised databased for monitoring key prehabilitation activities. However, personalised, categorised, and non-personalised data failed to achieve 50% recognition for two tasks (staircase and step up). Even though the system failed to recognize some activities, it still could detect and accumulate the intensities of each activity. This is important because the intensity of exercise, irrespective of type activity, is one of the most important factors that contributes to improving aerobic fitness.

In addition, the investigation of packet loss, range, and maximum WSD in a real-world cyber-physical system scenario showed that the system was able to provide up to five users concurrent WSD service without significant latency in both the gateway and the cloud. The cyber-physical system also demonstrated the ability to support a mixed mode pre-rehabilitation program in supervise indoor and unsupervised outdoor settings using the portable and base station gateway. Furthermore, the mixed mode prehabilitation programme before the surgery time frame led to improvements in 6MWT distance in those individuals who were had poor functional walking capacity. However, these findings need to be substantiated with more accurate measures of fitness.

Chapter 7 Conclusions and Future Work

7.0 Introduction

The proposed mixed mode prehabilitation model with the support of a remote monitoring system approach is a potential initiative for the healthcare sector to monitor the patient's prehabilitation programme wirelessly. This could facilitate acquired data analysis in a hospital environment and avoid the situation where patients have to be present at the hospital. Over the last decade, there has been growing scientific evidence supporting the use of prehabilitation in the context of cancer surgery [16]. Exercise training at home and in public facilities prior to surgical intervention (prehabilitation) has helped people maintain their functional ability and heal faster after surgery [14, 19, 20]. Most existing prehabilitation programmes have been conducted in hospitals and physiotherapy centres under the supervision of an experienced clinician.

The mixed mode prehabilitation paradigm enabled by design and execution of the CPS will be the focus of this chapter. The features and performance of both the mixed mode prehabilitation model and the CPS will be discussed in Section 7.1, Conclusions, with different design components conducting the CPS. Section 7.2 will discuss how the thesis work could be expanded in some fields to improve patient monitoring outcomes by embedding additional code and adding additional features to the various parts of the system.

7.1 Conclusions

The main contributions of the thesis can be divided into three parts. The first part is constructing a mixed mode prehabilitation programme by making use of two existing models, and extracting the advantages and eliminating the disadvantages of those models.

A mixed mode prehabilitation model was developed that took into consideration the advantages of supervised and unsupervised models in terms of flexibility, cost reduction, patient motivation, and assurance of performing the prescribed physical activities. The disadvantages of the supervised and unsupervised programmes have been minimised in this mixed mode model. For example, in a supervised programme, multiple visits to the hospital or physiotherapy centre may be required, while in an unsupervised programme, a lack of supervision means there is uncertainty about performing the prescribed physical activities.

The model benefits from both existing standard methods in prehabilitation and the potential of IoT technologies. Reduction of drawbacks like long waiting lists, inaccessibility for those individuals in remote geographical areas, limited resources, and the burden on both the healthcare system and patients have been considered in this model. The mixed mode model has attracted less attention than other existing models. There are no specific mixed prehabilitation models utilising IoT technology discussed in previous studies. The new model incorporates elements of previous programmes, such as the undertaking of physical exercise prescribed by the clinician in both supervised and unsupervised settings. Factors like the duration of bed rest, threshold time, and intensity level have been included in this model. Mathematical formulas have been created to express the mixed mode prehabilitation programme in numerical ways. The formulas show the effort, intensities, time, and type of physical activity by accumulating credit gain per single or multiple sessions. This mathematical model tends to support the mixed mode prehabilitation programme with regard to structuring the essential boundaries to achieve tangible results. As a result, the system will be able to convert physical effort into a numerical value (credit point). Using this credit points system enables patients and healthcare providers to track prehabilitation progress by comparing what was planned with what was accomplished. However, more investigations are required for the calculation of activity weight, as they resemble the same weight at this stage. Case study information from this thesis has also revealed that implementation of the mixed mode prehabilitation programme showed improvements in functional walking capacity during the 6MWT after six weeks of prehabilitation.

The second part of the thesis was database selection management, which has a significant impact on the percentages (accuracy) of various physical activity recognitions. The study shows that the databases could be classified into three types. The first type is a personalised database that is developed from individualised data collected from the same person who performed specific prehabilitation activities. This personal database offers higher percentages of activity recognition. Furthermore, this type of database was able to accurately recognise exercise intensity in a number of prehabilitation activities. This means that once the physical activity has been recognised, an intensity index value (low = 0.75, moderate = 1, vigorous = 2) could be recorded and contribute to the total output gain credit. The key advantage of this system over traditional accelerometry systems in prehabilitation that use step count is the ability to recognise and quantify the type and intensity of activity.

The second type of database is a categorised database. The current study shows that the output data components have similar features for certain groups of subjects, such as same age groups, fitness level, and health conditions, which can be used to develop a categorised database. A categorised database could be helpful to reduce the number of iterations required for updating a database during the mixed mode prehabilitation programme. It was shown that a categorised database showed slightly lower performance than a personalised database in terms of activity recognition.

The third type of database trialled in the thesis was non-personalised, which is the data gathered from different subjects while performing different physical exercises. The development of a categorised database could be beneficial for those patients who are unable to attend an initial supervised session in order to develop a personalised database. The system showed low recognition performance in comparison with personalised and categorised databases. This could be partly due to the relatively low numbers of subjects used in the current study to develop this database. The future development of a more extensive database from a variety of patients undergoing prehabilitation has the potential to improve the accuracy of the system.

The third part of this thesis focused on using the IoT and CPS to support the above features. The cyber physical system was designed and implemented to support the mixed mode prehabilitation programme. This technology offers access for real-time remote monitoring and visualisation to patients and healthcare staff. Visualisation through IoT technology also offers motivation to the patient to implement the programme through the use of real-time feedback on progress throughout the prehabilitation period. The three tiers of the cyber physical system (WSD, gateway, and cloud) are used as the basis for this system's design. Different components of the cyber physical system were analysed and tested for system performance and capability to support the mixed mode prehabilitation model. The WSD was able to handle the extracted data during different physical activities in terms of data storage (raw and processed), data processing (filtered data, calibration and FFT processes), and data transmission bit rate and range. Findings from the thesis show that processed data (FFT data) transmitted from the WSDs to the gateway exhibit high performance in terms of packet loss, transmission data range, and bitrate transmission of non-processed data (raw data).

In addition, processed data (FFT data) received by the gateway was shown to maximise the number of concurrent processed received data from different WSDs and minimise the gateway processing time. Accordingly, the limitations of the gateway in dealing with simultaneous data received from multiple different WSDs were successfully overcome. The gateway was tested with five WSDs at the same time and was shown to be capable of data analysis, data storage, data processing and transmitting results to the upper level without significant delay. In addition, different logical methods (M1, M2, M3, and M4) for activity recognition were implemented and embedded at the gateway level. The system showed high performance, with activity recognition percentages ranging from 70%-94% when using the personalised database, as described earlier in this discussion. The cyber physical system also demonstrated the ability to support a mixed mode prehabilitation programme in different scenarios, which included outdoor and indoor settings (with the portable base station gateway in the patient's home, gymnasiums, and physiotherapy centres). Finally, the main achievement of this study is that it shows that the mixed mode prehabilitation model can be applied in real-life scenarios, which has the potential to significantly reduce costs for both the healthcare system and patients.

7.2 Future Work

In this thesis, the proposed concept of the cyber physical system for cancer patient prehabilitation has been developed and tested. However, the system is a prototype, and future research should focus on improving performance and modifying the system according to current trends.

There are several suggestions for future work to build upon the mixed mode prehabilitation cyber system model developed in this thesis. These include the following:

- **Artificial Intelligence (AI) Embedded and Edge-Computing Aspects**

In the current stage of development, the research concept relies nearly exclusively on the gateway as an edge IOT computing device, managing and processing various types of data between the lower-level WSD and the upper-level cloud (ThingSpeak platform). According to current research, the gateway can handle a variety of tasks simultaneously. AI could be an interesting feature to embed into the gateway [173, 174]. AI is one of the main factors that could increase the percentages of physical activity recognition and enhance overall system performance. AI, such as neural networking and deep learning, could aid in training the subject database and transitioning it from non-personalised to categorised, and then to personalised, without the need for human intervention. This would mean that each time a subject performs a prescribed physical activity, the system starts a comparison between the previous and current database. This information could be used to generate an algorithm that would then be able to predict a new database based on the training data, and the database would be updated accordingly. The integration of AI into the system could potentially reduce the need for healthcare worker or technician intervention to update the database, and decrease unnecessary health centre visits.

- **Smart WSD**

A smart WSD could result from the combination of powerful functionality and features for performing WSD, such as classifying the FFT processed data to identify preliminary activity recognition [175]. An additional WSD feature, such as measuring displacement [4], could significantly improve preliminary activity recognition by distinguishing between physical activity with directional motion action, such as walking, and motion with no displacement, such as walking on a treadmill. As a result, sending recognised data to the upper level (gateway) will significantly reduce incoming data processing time, and that may improve overall system performance.

- **Activity Weighting**

The given weight of the various physical activities has the same value in this study. As a result, the actual time spent on each physical activity and the intensity level are critical factors that will have a direct impact on the credit gain calculation. While the activity weight is assumed to be constant (as discussed in chapter 4), in real-life scenarios, each activity could have a different weight based on different factors, such as limb involvement (upper/lower or both). A high level of physical activity may result in a different weight than a low level. According to current research, some common physical activities, such as cross training and rowing, are common physical activities that most elderly people cannot sustain for more than two minutes at a time. As a result, different weight could be used to optimise the output gain credit and add realism to the mathematical model.

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Appendix

A.0 Approved Ethics Application

AUT

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology
D-88, Private Bag 92006, Auckland 1142, NZ
T: +64 9 921 9999 ext. 8316
E: ethics@aut.ac.nz
www.aut.ac.nz/researchethics

13 December 2019

Adnan Al-Anbuky
Faculty of Design and Creative Technologies

Dear Adnan

Re Ethics Application: **19/212 Cyber physical systems and cancer patient rehabilitation**

Thank you for providing evidence as requested, which satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC).

Your ethics application has been **approved in stages** for three years until 13 December 2022.

Non-standard conditions must be completed before commencing your study. Non-standard conditions do not need to be submitted to or reviewed by AUTEC before commencing your study.

This approval is for the first phase of the research only. Full information about future stages of the research needs to be submitted to and approved by AUTEC before the data collection for those stages commences.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC in this application.
2. A progress report is due annually on the anniversary of the approval date, using the EA2 form.
3. A final report is due at the expiration of the approval period, or, upon completion of project, using the EA3 form.
4. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form.
5. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
6. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.
7. It is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard.

AUTEC grants ethical approval only. You are responsible for obtaining management approval for access for your research from any institution or organisation at which your research is being conducted. When the research is undertaken outside New Zealand, you need to meet all ethical, legal, and locality obligations or requirements for those jurisdictions.

Please quote the application number and title on all future correspondence related to this project.

For any enquiries please contact ethics@aut.ac.nz. The forms mentioned above are available online through http://www.aut.ac.nz/research/researchethics

Yours sincerely,

Kate O'Connor

Executive Manager
Auckland University of Technology Ethics Committee

Cc: khalid.elnaime@aut.ac.nz; Grant Mawston

A.1 Approved the Extension of Age Range

AUT

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology
D-88, Private Bag 92006, Auckland 1142, NZ
T: +64 9 921 9999 ext. 8316
E: ethics@aut.ac.nz
www.aut.ac.nz/researchethics

7 September 2020

Adnan Al-Anbuky
Faculty of Design and Creative Technologies

Dear Adnan

Re: Ethics Application: **19/212 Cyber physical systems and cancer patient rehabilitation**

Thank you for your request for approval of amendments to your ethics application.

The amendment to the inclusion criteria (extension of age range) is approved.

I remind you of the **Standard Conditions of Approval**.

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC in this application.
2. A progress report is due annually on the anniversary of the approval date, using the EA2 form.
3. A final report is due at the expiration of the approval period, or, upon completion of project, using the EA3 form.
4. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form.
5. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
6. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.
7. It is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard.

AUTEC grants ethical approval only. You are responsible for obtaining management approval for access for your research from any institution or organisation at which your research is being conducted. When the research is undertaken outside New Zealand, you need to meet all ethical, legal, and locality obligations or requirements for those jurisdictions.

Please quote the application number and title on all future correspondence related to this project.

For any enquiries please contact ethics@aut.ac.nz. The forms mentioned above are available online through http://www.aut.ac.nz/research/researchethics

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: khalid.alnaime@aut.ac.nz; Grant Mawston

A.2 Participant Information Sheet (procedure and steps followed during data collection)

AUT

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Participation Information Sheet 1 and 2

Date Information Sheet Produced:

17th Jul 2019

Updated with required amendments on:

31st Oct 2019

Updated with required 2nd amendments on:

10th Dec 2019

Updated with required phase 2 on:

29 July 2020

Project Title

Cyber Physical Systems and Patient Prehabilitation (Pre-operative) : The Prehabilitation program

An Invitation

Hello, my name is Khalid Al Naime, and I am a PhD candidate in the School of Engineering, Computer and Mathematical Sciences at AUT University. I would like to invite you to take part in our research project called 'Cyber Physical Systems and Patient Prehabilitation: Here the term young, middle age and elderly people. Your participation in this project is voluntary and you may withdraw at any time prior to the completion of data collection.

What is the purpose of this research?

The purpose of this research is to design a sensor, that can monitor physical activity (walking, cycling, rowing, step up, cross trainer and staircase). This device will ultimately be used to assess such activity in people undergoing abdominal surgery. The first phase of this research focuses on developing this sensor is to recognise variant different types of activities/exercises involved during the prehabilitation program for abdominal patients. The recognition will be based on the real-time data collected from the sensor. Phase one was successfully finished without any issue. Following phase two, will concern the transmission of signals to the internet and the subsequent presentation of the data in software.

How was I identified and why am I being invited to participate in this research?

You will have responded to an advertisement about the study. This is the first phase of data of data collection to establish healthy participant normative values for comparison with subsequent patient data. In this phases, participants of any gender should be healthy with no significant illness (e.g.

stroke, heart attack, breathing disorder). For this initial phase of the research, you may be excluded from participating if your health status indicates that the exercises you will performed may put too much stress on your body due to a neurological or musculoskeletal condition or are unable to communicate or understand English. You will also be required to complete a Physical Activity Readiness Questionnaire (PAR-Q) following consent. This is a health questionnaire to ensure you have no medical reason that may prevent you from participating in the activities performed in the study. If a medical problem is identified, you will be asked to see your general practitioner (GP) for medical clearance to perform the activities in the study.

What will happen in this research?

If you participate in phase 1 of this project, you will be asked to attend a data collection session at the private gym at North Shore AUT campus on Akoranga Drive AA109. You are welcome to bring family members or extended whānau to this session. During these sessions you will be required to perform certain sets of exercises (e.g., biking, rowing, cross trainer) and walking at low (light), moderate (light-somewhat hard) and vigorous (somewhat hard to hard) effort while wearing a wearable sensor at the ankle joint as shown in figure 1 below, the attached pictures. The researcher will ask you if there are any specific cultural needs (e.g., karakia) that you would like to be taken into consideration prior to fitting the sensor and performing the exercises. The wearable sensor device measures fast changes in movement. Mathematic analysis of the movements detected by the sensor is used to identify the different activities you are performing. The device can be worn at any side of the foot depending on your comfortability. The exercises are performed at a low moderate, and vigorous level of exertion and you will get rest breaks as you need them. Overall, the tests should not take longer than 45 minutes. Notes will be recorded by the researcher on the type and level of intensity of exercise you perform during the 45-minute session. The device will be removed at the end of the session and data recorded during your session will be then subsequently analysed by the researcher.

Figure 1 Wearable Device

Prehabilitation Activity Monitoring log Shhet Diary						
Participant (Patient) name: Age: Gender: Channel No:						
Day	**Date dd/mm/yy**	**Time H:M (PM/AM)**	**Period (minutes)**	**Type of the exercise**	**Intensity (L,M,V)**	**Location/AUT Lab home/GYM/outdoor**
1	**12/09/2020**	**8:25:00 AM**	**25**	**Walking**	**M**	**Outdoor**
1	**12/09/2020**	**10:30:00 AM**	**10**	**Cycling**	**M**	**Home**
1	**12/09/2020**	**1:00:00 PM**	**5**	**Rowing**	**L**	**Home**
2						
3						
4						
5						

Figure 2 Activity Diary Sample

What are the discomforts and risks?

There are no major risks associated with this testing, as it is non-invasive and safe. Tests are designed to mimic normal activities of prescribed physical exercises (e.g., walking, stairs, squatting, cycling, rowing) so are unlikely to cause any discomfort. You might feel some discomfort from the device, and this would normally be a skin irritation. In phase 1 in the lab, we will ask you often how the sensor feels. In phase 2, while using it at home, we will call you every couple of days to ask whether the device is comfortable.

How will these discomforts and risks be alleviated?

If you consider any of the movements excessively painful, you can stop at any time and remove the sensor or ask for our help. Similar tests have previously been done without any adverse effects, however a physiotherapist who has the appropriate knowledge and skills in dealing with prehabilitation will be involved in the different phases, and therefore can provide you with advice if required. If your skin is affected by wearing the sensor, you can remove it.

What are the benefits?

You will not receive direct benefit from participating in this research. The project outcomes will provide us with more information about the relationships between activity recognition, accuracy and functional mobility associated with activities undertaken in prehabilitation period before surgery. Overall, these findings could lead to new and improved monitoring of exercise treatment during the prehabilitation and will help in completion of a PhD research degree.

What compensation is available for injury or negligence?

In the unlikely event of a physical injury as a result of your participation in this study, rehabilitation and compensation for injury by accident may be available from the Accident Compensation Corporation (ACC), providing the incident details satisfy the requirements of the law and the Corporation's regulations.

How will my privacy be protected?

You will be given a code upon entry to the study and your name will not be used. The consent form, which will contain both your name and code, will be stored in a locked filing cabinet and kept separate from the study. No individual results will be identifiable in the study.

What are the costs of participating in this research?

The cost of participating in this project will be your time. In phase 1, the data collection time is expected to last approximately 45 minutes. In phase 2, you will wear the sensor continuously for one to four weeks.

What opportunity do I have to consider this invitation?

When you contact us, you will be able to chat about the study, and if you are interested you will be sent an information sheet. After receiving the information sheet, you have up to 7 days to let us know if you want to participate in the study.

How do I agree to participate in this research?

You will need to complete a consent form at the beginning of the data collection session. This session will be scheduled after you have told us that you would like to participate.

Will I receive feedback on the results of this research?

A one-page summary of the study results will be sent upon completion of the project. There will be a section in the Consent Form to indicate if you would like to receive this information.

What do I do if I have concerns about this research?

Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor, Grant Mawston, *grant.mawston@aut.ac.nz*, +64 9 921 9999 ext 7180 or Adnan-Al-Anbuky, *adnan.anbuky@aut.ac.nz*, +64 9 921 9999 ext. 9836

Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTEC, Kate O'Connor, *ethics@aut.ac.nz*, 921 9999 ext. 6038.

Whom do I contact for further information about this research?

Researcher Contact Details:

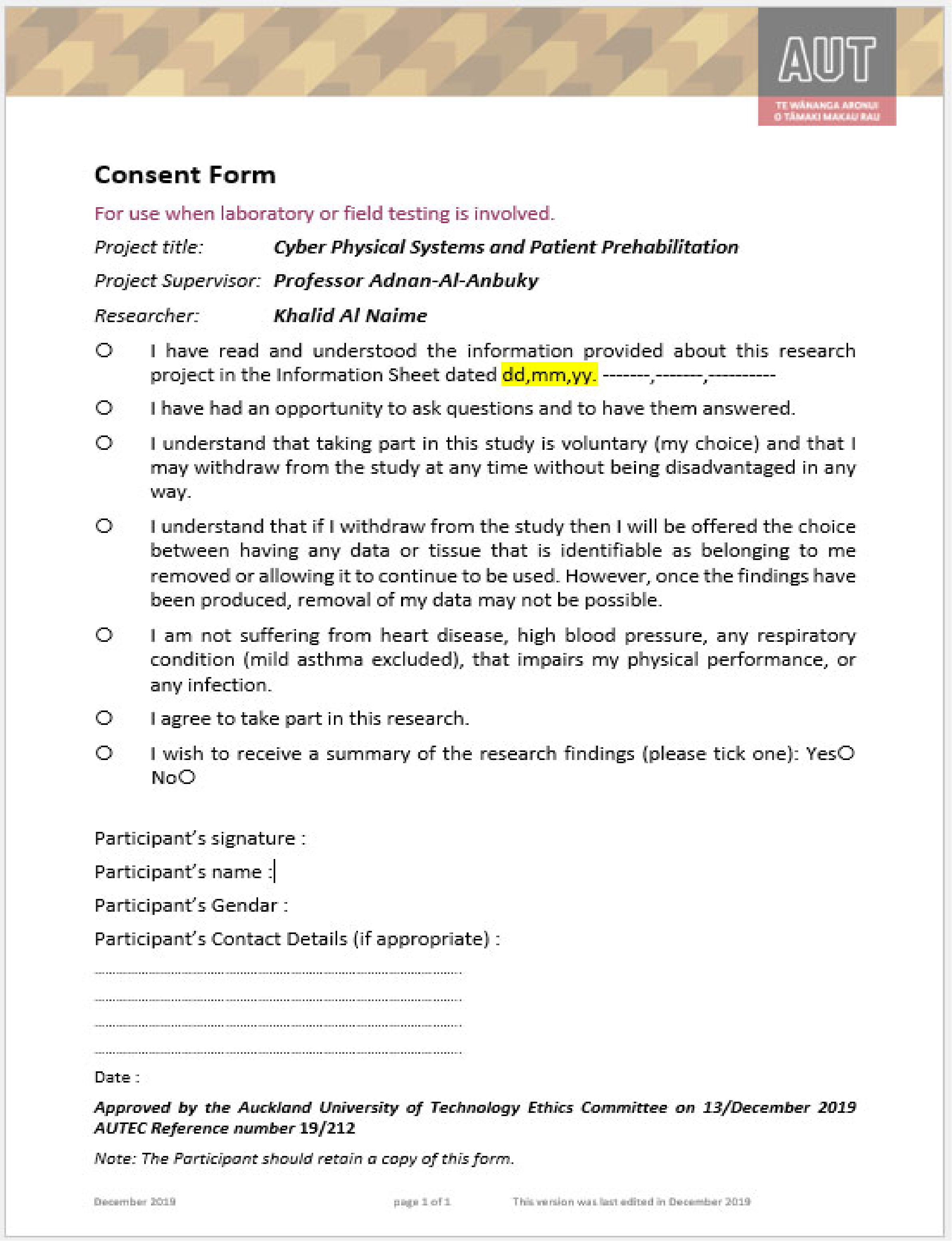
Khalid Al Naime, AUT University City Campus
Ph: 02108570417
Email: khalid.alnaime@aut.ac.nz

Project Supervisor Contact Details:

Dr. Grant Mawston, AUT University North Shore Campus
Ph: +64 9 921 9999 ext. 7180
Email: *grant.mawston@aut.ac.nz*

Professor Adnan-Al-Anbuky, AUT University City Campus
Ph: +64 9 921 999 ext. 9836
Email: adnan.anbuky@aut.ac.nz

A.3 Consent Form



Consent Form

For use when laboratory or field testing is involved.

Project title: ***Cyber Physical Systems and Patient Prehabilitation***

Project Supervisor: ***Professor Adnan-Al-Anbuky***

Researcher: ***Khalid Al Naime***

○ I have read and understood the information provided about this research project in the Information Sheet dated dd,mm,yy. -------,-------,----------

○ I have had an opportunity to ask questions and to have them answered.

○ I understand that taking part in this study is voluntary (my choice) and that I may withdraw from the study at any time without being disadvantaged in any way.

○ I understand that if I withdraw from the study then I will be offered the choice between having any data or tissue that is identifiable as belonging to me removed or allowing it to continue to be used. However, once the findings have been produced, removal of my data may not be possible.

○ I am not suffering from heart disease, high blood pressure, any respiratory condition (mild asthma excluded), that impairs my physical performance, or any infection.

○ I agree to take part in this research.

○ I wish to receive a summary of the research findings (please tick one): Yes○ No○

Participant's signature :

Participant's name :

Participant's Gendar :

Participant's Contact Details (if appropriate) :

....

....

....

....

Date :

***Approved by the Auckland University of Technology Ethics Committee on 13/December 2019 AUTEC Reference number* 19/212**

Note: The Participant should retain a copy of this form.

December 2019 page 1 of 1 This version was last edited in December 2019