


# Rehabilitation through Exercise Prescription for Cardiac Patients using an Artificial Intelligence-based Programme

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# II. Statement of Originality

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11th of July 2025
Pasan Witharana

For my parents and sister

# III. Acknowledgements

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Most of all, this project wouldn't have been possible without the voluntary participation of the patients. I am thankful for their role in this study and for their desire to contribute to the advancement of Medicine.

To all mentioned here and to those whose contributions may not be named but are deeply valued — thank you.

"If a machine can think, it might think more intelligently than we can. And then where would we be?"

Alan Turing, 1951

# IV. Abstract

Cardiac rehabilitation (CR) has been demonstrated to reduce morbidity and mortality following acute coronary syndrome and cardiac surgery. However, participation rates remain low due to barriers including transport difficulties, scheduling difficulties with work commitments, and fear of infection. Additionally, hospitals may also struggle to accommodate patients within the recommended time frame when short-staffed. An artificial intelligence (AI)-enabled mobile application for home-based CR may address these challenges.

This research aimed to determine the feasibility of conducting a large-scale definitive randomised controlled trial (RCT) to assess the effectiveness of an AI-powered home-based CR programme. The primary objective was to develop and evaluate a mobile application capable of automatically prescribing personalised physical activity goals using a preliminary machine learning model prior to conducting the feasibility RCT.

I followed an evidence-based approach to develop a mobile application, web portal, and machine learning algorithm using real-life data from CR patients. The intervention underwent alpha testing with hospital staff, followed by usability testing in cardiac patients (n=15), and concluded in a feasibility RCT (n=51) employing a mixed-method approach. Predefined feasibility criteria were established for patient recruitment (≥70%), randomisation (≥80%), drop-out (≤20%) and adherence (≥75% weekly application usage). Additionally, a qualitative assessment of trial delivery was conducted.

The results demonstrated that all feasibility targets were exceeded: 85% recruitment rate, 100% randomisation rate, 86% retention rate, and 92% weekly application adherence. The mobile application achieved excellent usability scores (82.5/100) across participants with varying technological abilities. No adverse events were reported, and AI-prescribed goals required no manual adjustment by healthcare professionals. Qualitative data confirmed strong feasibility for trial delivery.

## Introduction

The intervention successfully automated exercise prescription while addressing key barriers to traditional CR participation, providing a foundation for future large-scale effectiveness trials and for the development of a definitive machine learning model.

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# VIII. List of Abbreviations

| | |
|---|---|
| **ACs** | Activity Counts |
| **AHA** | American Heart Association |
| **AI** | Artificial Intelligence |
| **AHRQ** | Agency for Healthcare Research and Quality |
| **ACS** | Acute Coronary Syndrome |
| **API** | Application Programming Interface |
| **BACPR** | British Association for Cardiovascular Prevention and Rehabilitation |
| **BCT** | Behavioural Change Techniques |
| **BMI** | Body Mass Index |
| **CABG** | Coronary Artery Bypass Grafting |
| **CAD** | Coronary Artery Disease |
| **CGS** | Curved Grading Scale |
| **CHD** | Coronary Heart Disease |
| **CFS** | Clinical Frailty Scale |
| **COVID-19** | Coronavirus Disease 2019 |
| **CR** | Cardiac Rehabilitation |
| **CTGAN** | Conditional Tabular Generative Adversarial Network |
| **CVD** | Cardiovascular Disease |
| **DASS21** | Depression, Anxiety, and Stress Scale |
| **DHI** | Digital Health Interventions |
| **DL** | Deep Learning |
| **DVLA** | Driver and Vehicle Licensing Agency |
| **eHealth** | Electronic Health |
| **EQ5D5L** | EuroQOL 5-Dimensions |
| **EUROASPIRE** | European Society of Cardiology |
| **GSCV** | Grid Search Cross-Validation |
| **HADS** | Hospital Anxiety and Depression Scale |
| **HCP** | Healthcare Professional |
| **HF** | Heart Failure |
| **IHD** | Ischemic Heart Disease |

| | |
|---|---|
| **iOS** | iPhone Operating System |
| **LPA** | Light Physical Activity |
| **MAE** | Mean Absolute Error |
| **MAUQ** | Mobile Application Usability Questionnaire |
| **MEDLARS** | Medical Literature Analysis and Retrieval System |
| **METs** | Metabolic Equivalent of Task |
| **mHealth** | Mobile Health |
| **MI** | Myocardial Infarction |
| **ML** | Machine Learning |
| **MLHFQ** | Minnesota Living with Heart Failure Questionnaire |
| **MVD** | Multivessel Disease |
| **MVPA** | Moderate to Vigorous Physical Activity |
| **NACR** | National Audit of Cardiac Rehabilitation |
| **NHS** | National Health Service |
| **NICE** | National Institute for Health and Care Excellence |
| **NPT** | Normalisation Process Theory |
| **NSTEMI** | Non-ST-Segment Elevation Myocardial Infarction |
| **PA** | Physical Activity |
| **PAM** | Physical Activity Monitoring |
| **PCI** | Percutaneous Coronary Intervention |
| **PICO** | Population, Intervention, Comparison, Outcome |
| **PRISMA** | Preferred Reporting Items for Systematic Reviews and Meta-Analyses |
| **QOL** | Quality of Life |
| **RCT** | Randomised Controlled Trial |
| **RECAP** | Rehabilitation through Exercise Prescription for Cardiac patients using an Artificial Intelligence based Programme |
| **RF** | Random Forest |
| **RFE** | Recursive Feature Elimination |
| **RFECV** | Recursive Feature Elimination with Cross-Validation |
| **RMSE** | Root Mean Square Error |
| **ROB** | Risk of Bias |
| **ROBINS I** | Risk of Bias in Non-Randomized Studies of Interventions |
| **RPE** | Rating of Perceived Exertion |

| | |
|---|---|
| **SCT** | Social Cognitive Theory |
| **SD** | Standard Deviation |
| **SDLC** | Software Development Life Cycle |
| **SF36** | 36-item Short Form Survey |
| **SSL** | Secure Sockets Layer |
| **STEMI** | ST-Segment Elevation Myocardial Infarction |
| **SUS** | System Usability Scale |
| **UI** | User Interface |
| **UK** | United Kingdom |
| **US** | United States |
| **VO2** | Oxygen Consumption |
| **WHO** | World Health Organization |
| **6MWT** | 6-Minute Walk Test |
| **6MWTD** | 6-Minute Walk Test Distance |

# IX. Peer-reviewed Publications

**Arising directly from the thesis, with direct extractions within the thesis (referenced at the beginning of each chapter)**

1. Witharana P; Chang L; Maier R;Ogundimu E;Wilkinson C;Athanasiou T;Akowuah E; 2024 Feasibility Study of rehabilitation for cardiac patients aided by an artificial intelligence web-based programme: A randomised controlled trial (RECAP trial)-a study protocol, BMJ open. Available at: https://pubmed.ncbi.nlm.nih.gov/38688664/ (Accessed: 16 August 2024). (1)

**Conference Abstract Publications**

2. Witharana, P., Chang, L., Maier, R., Ogundimu, E., Wilkinson, C., Athanasiou, T. and Akowuah, E. (2024) 'Usability testing of an artificial intelligence enhanced mobile application for home-based cardiac rehabilitation', BMJ Heart, 110(Supplement 5), A15.1. Available at: https://heart.bmj.com/content/110/Suppl_5/A15.1 (Accessed: 2 June 2025). (2)

3. Witharana, P., Chang, L., Maier, R., Athanasiou, T. and Akowuah, E. (2024) 'Development and evaluation of the RECAP trial mobile application and web portal: preliminary testing on healthy volunteers', BMJ Heart, 110 (Supplement 5), A14.2. Available at: https://heart.bmj.com/content/110/Suppl_5/A14.2 (Accessed: 2 June 2025). (3)

**Submitted for Publication – Major changes**

4. Approaches to mobile application facilitated Cardiac Rehabilitation: A Systematic Review. JMIR Cardio Journal. 2025

# X. Selected Presentations

**Presentations arising from thesis to date**

1. A feasibility study of Rehabilitation for Cardiac patients aided by an Artificial Intelligence-web based Programme: A Randomised Controlled Trial (RECAP Trial). Witharana P; Chang L; Maier R;Ogundimu E;Wilkinson C;Athanasiou T;Akowuah E. Society for Cardiothoracic Surgery, Annual Conference 2024, Cardiff, UK, 2024

2. Approaches to Mobile App-based Cardiac Rehabilitation: A Systematic Review. Witharana P; Sherif M; Shafiq U; Wilkinson C; Athanasiou T; Akowuah E. Society for Cardiothoracic Surgery, Annual Conference 2024, Cardiff, UK, 2024

3. Usability testing of an artificial intelligence enhanced mobile application for home-based cardiac rehabilitation. Pasan Witharana, Chang, L., Maier, R., Ogundimu, E. and Akowuah, E. BACPR Annual Conference 2024, Manchester, UK, 2024

4. Development and evaluation of the RECAP trial mobile application and web portal: preliminary testing on healthy volunteers. Pasan Witharana, Chang, L., Maier, R., Athanasiou, T. and Akowuah, E. BACPR Annual Conference 2024, Manchester, UK, 2024

5. Results from the Phase II of RECAP (Rehabilitation through Exercise Prescription for Cardiac patients using an Artificial Intelligence based Programme) Trial: A Feasibility RCT. Witharana P; Chang L; Maier R;Ogundimu E;Wilkinson C;Athanasiou T;Akowuah E. Society for Cardiothoracic Surgery, Annual Conference 2025, March 16-18, 2025, EICC, Edinburgh, 2025

**Accepted for presentation as poster**

1. Hospital versus home-based cardiac rehabilitation augmented by accelerometery and Artificial Intelligence: Results, a Feasibility RCT. Witharana P; Chang L; Maier

R;Ogundimu E;Wilkinson C;Athanasiou T;Akowuah E. 39th EACTS Annual Meeting, October 8-11, 2025, Copenhagen, 2025

# XI. Exact Details of Contributions

I have carried out the work presented in this thesis. However, due to the nature of research and the need for rigorous methodology, other personnel have been involved in carrying out certain aspects of the work. The nature and extent of these contributions are described below.

**Chapter 1: Introduction**
Concept by PW and EA, Written by PW, Supervised by EA, TA, RM and LC

**Chapter 2: Approaches to Mobile Application based Cardiac Rehabilitation: A Systematic Review**
Concept by PW and EA, Written by PW, Supervised by EA, CW, TA, RM and LC
Second screening of articles included in systematic review by MS, risk of bias analysis by US

**Chapter 3: Development of a Machine Learning Algorithm for Physical Activity Goal Prescription**
Concept by PW and EA, Written by PW, Supervised by EA, QC, RM, LC and TA

**Chapter 4: Development of the Mobile Application for Patients and Web Portal for Staff and Initial Evaluation**
Concept by PW and EA, Written by PW, Supervised by EA, RM, LC and TA
Participant interviews conducted by PW. Qualitative interviews coded by PW and reviewed by JT.

**Chapter 5: Evaluation of the Mobile Application and Web-portal on patients referred for Cardiac Rehabilitation**
Concept by PW and EA, Written by PW, Supervised by EA, RM, LC, TA, EO and SH

One qualitative staff focus group conducted by PW and JT. The other staff focus group and patient interviews conducted by PW. Qualitative interview coding and analysis done by PW, AG and JT. Qualitative analysis oversight by SH.

**Chapter 6: RECAP Trial: Results from the Feasibility Randomised Controlled Trial**
Concept by PW and EA, Written by PW, Supervised by EA, RM, LC, TA, EO and SH
Participant recruitment and conducting study visits by PW

**Chapter 7: Exploring Patient Experiences in the RECAP Trial: A Qualitative Evaluation**
Concept by PW and EA, Written by PW, Supervised by EA, SH, RM, LC and TA
Participant interviews conducted by PW, AG and JT. Qualitative interview coding and analysis done PW, AG and JT. Oversight by SH.

**Chapter 8: General Discussion and Conclusion**
Concept by PW and EA, Written by PW, Supervised by EA, RM, LC and TA

**Key**
PW: Pasan Witharana
Enoch Akowuah (EA), Thanos Athanasiou (TA), Rebecca Maier (RM), Lisa Chang (LC), Emmanuel Ogundimu (EO), Samantha Harrison (SH), Qin Chen (QC), Chris Wilkinson (CW), Mohamed Sherif (MS), Umar Shafiq (US), Jason Trevis (JT), Adam Gatherar (AG), Jun Tan (JT)

# CHAPTER 1

# 1. Introduction

## Key Learning Points from this Chapter

- Cardiovascular disease continues to be the leading cause of death globally.
- Secondary prevention, including cardiac rehabilitation (CR), has been shown to reduce morbidity and mortality and improve patients' quality of life.
- However, uptake and participation in CR are limited by factors such as transport access, patients' schedules not aligning with traditional hospital-based CR session timings, fear of infection, and socioeconomic factors.
- Advances in digital health, including mobile applications, physical activity monitoring devices, artificial intelligence (AI), and machine learning (ML), may be used for remote monitoring, personalised exercise prescription and improving engagement.

Introduction

- This research aims to develop, evaluate and assess the feasibility of a clinician-led home-based CR programme facilitated by an AI-enabled mobile application for personalised exercise prescription, with an evidence-based approach for technology development, usability testing, and a mixed-methods feasibility randomised controlled trial.

## 1.1 The Growing Burden of Cardiovascular Disease

Cardiovascular disease (CVD) is the most common cause of death worldwide, with an estimated global disease burden of 17.8 million deaths due to CVD in 2017. Ischaemic heart disease accounts for almost 50% of these deaths (4). Although age-standardized rates of cardiovascular disease (CVD) mortality and incidence have shown significant decreases over time, the absolute number of individuals affected by CVD continues to rise due to population growth and ageing. The recent slowing of declines in atherosclerotic cardiovascular diseases and the increasing absolute burden pose significant challenges for health systems and resource allocation (5).

The progression of coronary heart disease (CHD) is a gradual journey driven by ongoing chronic inflammation, suggesting that there exists a timeframe where interventions can effectively manage CHD risk before it fully materializes (6).

Coronary heart disease (CHD) may occur at a young age or in later life. The onset of CHD at an early age is preventable mainly because many of its risk factors are within our control and can be modified. These include hypertension, high cholesterol levels (hyperlipidaemia), diabetes, tobacco smoking, physical inactivity, excess weight, and obesity (7). Moreover, individuals with early-onset coronary heart disease exhibit a higher prevalence of psychological stress, anxiety, excessive workloads, and unhealthy dietary patterns, notably an intake of high-calorific foods, in contrast to those experiencing CHD later in life (8). Chronic risk factors such as hypertension, diabetes mellitus, and stroke typically manifest later in life and play a role in the development of late-onset CHD (7). Modifying these risk factors will reduce the likelihood of an individual developing CHD.

CHD may also make an individual more prone to other diseases, such as COVID-19. The long-term impact of the COVID-19 pandemic on CVD trends remains uncertain (5). Individuals with pre-existing coronary heart disease are more likely to experience severe COVID-19 compared to those without coronary heart disease, with hypertension influencing this association. Therefore, people with coronary heart disease must prioritize self-prevention

to reduce the risk of infection. Additionally, doctors should closely monitor COVID-19 patients with coronary heart disease to prevent adverse events (9).

Treatment for CHD may include lifestyle changes such as regular exercise, medication, angioplasty, or surgery (10). Percutaneous coronary intervention (PCI) stands as the primary reperfusion strategy for acute myocardial infarction (MI). Yet, coronary artery bypass grafting (CABG) remains a secure and effective alternative, particularly for patients with ST-segment elevation MI (STEMI) and non-ST-segment elevation MI (NSTEMI) (11). This is particularly true in cases of unsuccessful PCI or when severe multivessel disease (MVD) is present (11).

A diagnosis of CHD can significantly impact a patient's life, encompassing both physical and mental health ramifications. In 2014, the American Heart Association issued a scientific statement identifying depression as a significant risk factor for cardiac morbidity and mortality following acute coronary syndrome (12). A prominent meta-analysis led by researchers from the Netherlands discovered that depression is associated with a 2.7-fold higher risk of cardiac-related mortality, a 2.3-fold higher risk of all-cause mortality, and a 1.6-fold higher risk of cardiovascular events within the two years following an acute myocardial infarction (MI) (13).

Secondary prevention is crucial following a diagnosis of CHD. One of the key components of secondary prevention is cardiac rehabilitation (CR) (14).

### 1.1.1 Secondary prevention of cardiovascular disease

The National Institute for Health and Care Excellence (NICE) recommends secondary prevention strategies to mitigate the risk of complications and subsequent cardiovascular events in individuals who have experienced a myocardial infarction (MI) (14). NICE advises healthcare providers to offer patients a comprehensive CR programme, ensure ongoing prescription and monitoring of secondary prevention medications, provide lifestyle guidance covering diet, physical activity (PA), alcohol consumption, smoking cessation, and weight management, and optimize the management of other modifiable risk factors or conditions such as hypertension and diabetes (14).

NICE recommends that people who have had an MI should be offered medication management with angiotensin-converting enzyme (ACE) inhibitors, dual antiplatelet therapy, a beta blocker and a statin as appropriate (14). Dual antiplatelet therapy provides superior cardiac protection compared with aspirin alone for patients following ACS or those undergoing PCI (15).

The American Heart Association (AHA) recognized the broader concept of health beyond disease absence in defining Cardiovascular Health (CVH) 2010, aiming for a universally accessible and actionable definition. Initially based on seven health behaviours and factors, termed Life's Simple 7, optimal CVH was linked to better cardiovascular outcomes and quality of life. Over the past 12 years, evidence supporting this construct has led to an update called Life's Essential 8, which includes sleep as a new component to enhance CVH measurement and promote individual and population health improvement. Life's Essential 8 comprises the eight elements essential for cardiovascular health: maintaining a healthy diet, engaging in regular PA, abstaining from nicotine, ensuring healthy sleep patterns, maintaining a healthy weight, and keeping blood lipids, blood glucose, and blood pressure levels within a healthy range (16).

Increasing PA is a crucial aspect of secondary prevention. People who are active have been shown to have a significantly reduced risk of developing ischaemic heart disease (17). Furthermore, PA has also been shown to decrease the risk of developing other conditions such as ischaemic stroke, breast cancer, colon cancer, diabetes, and all-cause dementia (17, 18).

Following a cardiac event, patients should be encouraged to exercise and increase their PA. A structured approach to achieving this is by referring them to a CR programme.

## 1.2 Cardiac Rehabilitation Programmes

CR is an organized and systematic programme designed to tackle the root causes of cardiovascular disease (CVD) and enhance both physical and mental well-being following a

myocardial infarction (MI), as recommended by NICE guidelines (14). According to the British Association for Cardiovascular Prevention and Rehabilitation (BACPR), CR is defined as 'The coordinated sum of activities required to influence favourably the underlying cause of cardiovascular disease, as well as to provide the best possible physical, mental and social conditions, so that the patients may, by their efforts, preserve or resume optimal functioning in their community and through improved health behaviour, slow or reverse progression of disease' (14).

CR promotes a healthy lifestyle, which helps slow the progression of heart disease and reduces the risk of premature death, particularly from MI or stroke. It is one of the most thoroughly researched models of long-term condition management, with strong clinical evidence supporting its effectiveness (14). This programme is cost-effective, lowering unplanned readmissions for cardiac issues and improving outcomes for individuals with CVD (14).

A meta-analysis encompassing 85 randomized controlled trials (RCTs) with a total of 23,430 coronary heart disease (CHD) patients substantiated the clinical benefits of exercise-based CR (19). These benefits include reductions in cardiovascular mortality, MI, and hospitalization rates. Furthermore, the review provides current evidence affirming the generalizability of these benefits across diverse patient populations, within the context of modern medical management, and across various healthcare settings, including those in low- and middle-income countries.

Furthermore, CR could reduce hospital admissions and improve quality of life, reducing cardiovascular mortality (20). Improvements in health-related quality of life may be further enhanced in patients who remain physically active (21). NICE recommends that all individuals who have experienced an MI, regardless of age, should be informed about and offered a CR programme that includes an exercise component. CR after an MI, when it includes exercise, has been shown to reduce all-cause and cardiovascular mortality rates (14).

Comprehensive CR programmes should encompass health education, lifestyle advice, and stress management components. It is crucial to initiate CR in the hospital as soon as possible after admission and before discharge. The individual should be invited to an assessment

appointment within ten days of hospital discharge, with further sessions scheduled subsequently (14). Starting CR promptly after an MI greatly enhances attendance rates and clinical outcomes. Furthermore, an early assessment appointment ensures timely contact with a member of the CR team (14).

CR programmes should offer various options tailored to clinical needs, encouraging participation without excluding individuals who opt out of specific components. To promote adherence, these programs should be available at multiple venues, including the person's home, hospitals, and community centres, and at different times, including outside working hours (14).

CR has a long history spanning centuries (22). The medical benefit of exercise was first observed in the 18$^{th}$ and 19$^{th}$ centuries. Structured CR programmes, as they are currently offered, began to take shape in the early 20$^{th}$ century (22). Over the years, CR programmes have evolved to involve multifactorial interventions (22). They will continue to adapt to the changing needs of the global population. Research in the field of CR will fuel these changes and may help develop more effective programmes.

While rehabilitation, aims to re-establish functional capacity, facilitate return to daily activities and support adherence to secondary prevention strategies, prehabilitation aims to optimize functional capacity and risk profile to help patients better tolerate the intervention and hasten recovery (23). One meta-analysis found that prehabilitation prior to cardiac surgery has been associated with a significant impact on functional capacity as measured by the 6-minute walk test distance (24). It has also been shown to reduce length of hospital stay and risk of postoperative atrial fibrillation in patients 65 years old or younger (24). Although prehabilitation has an important role in patient optimisation, this thesis focuses on rehabilitation.

### 1.2.1 Components of a CR Programme

A CR programme may include exercise, information and education, peer support, and emotional well-being (Figure 1.1). The specific components of the programme will be based on the plan developed during the initial discussion and assessment with the CR team (25).

During the CR programme, patients may discuss various risk factors they wish to address, such as adopting a healthy diet, quitting smoking, or safely increasing PA levels (25).

Exercise sessions are customized to individual needs, abilities, and preferences. These sessions aim to enhance fitness, strength, and confidence safely. Additionally, guidance on maintaining PA at home daily is provided. The activities will depend on individual interests, local availability, and the team's recommendations. Exercise sessions might include group classes, walking programmes, or home-based routines. Generally, these sessions consist of three main parts: a warm-up, the main exercise, and a cool-down, with some sessions including a relaxation component at the end. The warm-up prepares the body and heart for the exercise session. The main exercise typically lasts longer than the warm-up and is conducted at a safe intensity level. Patients are explained how to monitor exertion, which may involve measuring heart rate or using a perceived exertion scale. Cooling down is essential to the session, helping the body gradually return to its pre-exercise state (25).




*Figure 1.1 Components of a CR Programme (1)*

After a diagnosis of a cardiac condition, it is common to experience a range of emotions, such as anger, frustration, and sadness. Feelings of confusion and isolation are also prevalent and can significantly impact the patient and their loved ones. CR provides advice and information on adjusting to life with a cardiac condition and managing mental health concerns or stress (25). CR classes may also offer patients a space to socialise and speak to other patients who are in a similar place to them.

There are multiple ways to participate in a CR programme. Options include attending in-person classes at a local facility, participating from home via online remote platforms or written programs, or combining both (25). Different centres across the UK may offer varying programs depending on local expertise and available resources.

Before commencing the CR programme, patients are invited to engage in a discussion with members of the local CR team. This preliminary meeting, often called an assessment, provides an opportunity to express concerns, articulate priorities, and collaboratively set both short-term and long-term goals (25). This allows patients to discuss any concerns they may have and develop a plan with the help of a healthcare professional (HCP).

### 1.2.2 Addressing Participation Gaps in Cardiac Rehabilitation: Barriers and Solutions

Despite the numerous benefits of CR, its uptake remains low (26). According to the EUROASPIRE III survey, only 37% of eligible patients participated in a CR programme (27). This issue is prevalent in the UK and affects other countries.

A study investigating barriers to CR found several factors associated with higher participation rates. These included younger age, male gender, absence of diabetes, STEMI diagnosis, receipt of reperfusion therapy, no history of previous MI, no prior attendance at CR, and being referred to CR while still in the hospital (28). Psychosocial factors influencing participation included the belief that CR is necessary, a perception of better health before the MI, the ability to drive, and a higher level of education (28).

A qualitative study on patients who dropped out of a CR programme revealed that the distress of experiencing a cardiac event made the significant lifestyle changes required by CR feel overwhelming (29). One of the critical challenges was adapting to new physical limitations, which contributed to the dropout rates. Many participants also experienced anxiety about the recurrence or progression of CHD, leading to reluctance to join public CR sessions. Additional factors influencing dropout included the distance to the programme, scheduling conflicts, and the absence of a personalized exercise plan. Due to work, family commitments, and long travel distances, participants often found it challenging to attend CR sessions at scheduled times.

Elderly patients may depend on their relatives for assistance with hospital visits. Patients who lived further away from the CR centre were less likely to attend a programme (30). Factors such as travel time, the location of the CR centre, travel costs, and the ability to drive all influence an individual's likelihood of participating in a CR programme (31).

The National Audit of Cardiac Rehabilitation (NACR) is a national audit conducted in the UK to evaluate and improve the quality of CR services. The NACR aims to improve the availability and uptake of cardiovascular prevention and rehabilitation services, promote best practices, and improve the overall quality of these services (32). Data from CR patients are collected at a national level, encompassing information such as medical history, demographics, and PA. This data is then uploaded to a secure online portal managed by NHS England. One of the aims of the NACR is to investigate the factors contributing to low participation rates, compare data across different programs, and identify areas for improvement (32).

According to the NACR Quality and Outcomes Report 2021 (33), the relative differences in participation rates for patient groups in 2020 and 2019 revealed significant reductions across several demographics. Participation rates dropped by 11% for patients from ethnic minority groups, 8.1% for males, and 5.9% for females. Patients from more deprived areas also experienced a decrease in participation rates by 3.3%. Furthermore, patients without additional long-term conditions saw a relative drop of 5.7% in their participation rates. Despite the larger relative decrease in participation rates for males compared to females in 2020, males continued to have higher overall CR participation rates than females.

In 2019, 16% of CR participants were enrolled in home-based programmes; however, in 2020, due to the impact of COVID-19, this figure increased to 76% (33). The COVID-19 period was particularly difficult for CR programmes as 12% of the programmes had their whole team redeployed to other hospital areas. In 2020, patients from deprived areas also exhibited lower participation rates in CR (33).

A systematic review and meta-analysis of factors associated with participation in CR programmes found that age, education level and income levels were deciding factors likely to influence an individual's involvement in CR (34). Individuals over 60 were less likely to participate in a CR programme, whereas those with a college education or higher were more likely to engage in a programme (34). This review also found that females are less likely to participate than males (34). There are several reasons why elderly patients are less likely to participate in CR. These include a poor understanding of what CR entails and its benefits, transport issues, and being a caregiver to another person at home (31). Conversely, Younger patients may be less likely to participate due to work commitments and lack of time in general (31). In addition to that, patients who smoked had a lower probability of participation, and they were also more likely to drop out of a CR programme (34).

One potential solution to the challenges encountered by traditional hospital-based CR programs is the implementation of home-based CR programs. Such a programme would increase patient accessibility by eliminating the need for long-distance travel and mitigating transportation issues. Home-based CR also allows patients to exercise conveniently rather than adhere to a fixed schedule. This approach would also benefit patients who are hesitant to attend public CR sessions.

### 1.2.3 Home-based Cardiac Rehabilitation Programmes

Delivering CR in the patient's home has several advantages. It could eliminate transportation challenges, potentially increasing participation in CR programs (31). A home-based CR programme may represent the optimal solution for patients who encounter challenges in attending a hospital programme scheduled on a specific day.

A systematic review of the safety and long-term outcomes of remote CR in CHD patients concluded that it could be a safe alternative to traditional CR even in the longer term (35). A systematic review of clinical outcomes in cardiac telerehabilitation over the past decade concluded that home-based CR could improve access to rehabilitation and enhance the long-term management of cardiovascular risk factors (36). Remote CR has the potential to increase the uptake of CR (35).

The NACR Quality and Outcomes Report 2021 found a 60% increase in the uptake of home-based CR compared to pre-pandemic times, where the uptake of home-based CR was only 10% (NACR reports 2016 to 2019) (33). This shift aligns with the NHS's goal of improving access to digitally enabled care (37). As per the NHS's ten-year plan, the NHS aims to offer a "digital first" option for most face-to-face consultations (37). This will allow patients to have thorough consultations with their clinicians in a way that suits them. It also aims to use AI to help healthcare professionals with decision-making using best practice principles. Moreover, the NHS Long-Term Plan emphasizes fostering a world-leading health IT industry while supporting software developers and innovators (37).

Moving the CR programme from the hospital setting to the patients' homes will allow CR to be offered to a broader group (38). Furthermore, AI may be used with wearable devices such as sensors to aid in the early detection of cardiac events (39). This could further improve the safety of home-based CR programmes (39). These programs could enhance their engagement and participation by providing patients with real-time access to data such as PA and health metrics (40).

Home-based CR programs may be delivered through mobile applications (apps), which can be a helpful link between hospital teams and patients.

## 1.3 Introduction to Mobile Applications and Digital Health Interventions

Digital health interventions (DHI) are increasingly used in medicine in cardiology, primary care, endocrinology, gynaecology, neurology, and ophthalmology (41). Digital health, which

may also be referred to as eHealth, is defined by the WHO as “the cost-effective and secure use of information and communications technologies in support of health and health-related fields, including health-care services, health surveillance, health literature, and health education, knowledge and research” (42). Digital health interventions can lead to better patient outcomes and may offer a cost-effective option compared to standard care (41).

There was an exponential increase in DHI, particularly during the COVID-19 pandemic, as it became one of the primary methods of healthcare delivery in response to global social distancing measures (43). An individual's level of digital health literacy may significantly influence their ability to utilize a mobile application effectively. Digital health literacy refers to a person’s ability to effectively engage with digital technology, applying health information specifically from electronic sources (44).

The development of mobile applications is a complex process involving various stages and considerations. These apps require detailed planning and implementation to meet the varying needs of patients. Mobile applications may be developed to work on platforms such as Android and iOS operating systems (45). Mobile apps can be programmed using several programming languages, including Python, PHP, Perl, Cocoa, Java, JavaScript and C (46). The development of a mobile app can take in excess of 36 weeks, and a team of over 40 is needed in some circumstances (46). The development process includes several stages, such as initial planning, prototype development and testing. During the initial planning stages, goals for the mobile app should be identified, taking into account the needs of the user (46). For example, an app aimed at teenagers may have a different architecture than an app aimed at the elderly. During the planning stages, the functionality of the app will be established. A draft of the graphical user interface will be created either by hand or using computer software, considering user interface design guidelines set out by mobile app stores such as iOS and Android before it is programmed (46).

Mobile app testing is another key component of app development as it allows early identification of any problems (referred to as “bugs” in software development) before making an app available to the users. There are various types of testing, including functional testing (ensuring the app is working as intended), performance testing (to check the performance of the app in conditions such as low mobile battery power), usability testing (to ensure that the app can achieve the intended goal) and installation testing (this checks if the app can be

successfully installed on a user's mobile phone) (47). Testing mobile apps can be challenging due to the varying responses different mobile devices may have to the same application.

User data storage is an essential component of many computer systems, including mobile apps. Mobile apps can store data on a user's device, allowing that data to be accessed by the user at any time in the future. This may include data such as their name, email address and password. However, many mobile apps that are currently available store data in other locations external to a user's mobile device, such as a cloud database. A cloud database allows data to be stored on a server (a programme or device that provides resources to another device or user), which may be installed worldwide (48). The user can then access this data even when they don't have access to their mobile device.

One example of a cloud database system is Cloud Firestore (49). Google manages Cloud Firestore and allows app development to be simplified as it enables storing, syncing and retrieval of data via a mobile app (49). The storage of data and its prompt retrieval are vital as they allow the personalisation of a mobile app. For instance, an application designed to recommend exercises based on a user's PA may require storing the user's PA data in a cloud-based database, enabling the retrieval and analysis of this information later.

While patients may use mobile apps as part of a DHI, a web portal could allow staff based at a hospital to monitor their patients remotely. The web portal could interface between the staff and the patients (50, 51). Furthermore, it could also facilitate notifications to patients' mobile phones. A systematic review of factors influencing adherence to mobile health apps for preventing or managing noncommunicable diseases found that notifications could promote adherence to management plans, including encouraging engagement in PA (52). A web portal may also be used to communicate with patients via direct messaging and allow clinicians to arrange patient appointments (53).

### 1.3.1 Advantages of Digital Health Interventions

DHI can offer several advantages to patients by improving access to healthcare services.

Digital Health Interventions (DHI) have the potential to enhance healthcare delivery by improving patient engagement, facilitating active participation in health management, and fostering better communication between patients and healthcare providers. By providing easily accessible mobile applications, DHI empowers patients to take greater control of their health (54). Mobile applications can offer patients personalised treatment plans, medication reminders, and lifestyle recommendations (54).

Personalization, primarily through providing helpful individual feedback, may improve the usability of mobile apps and increase patient engagement (55). Apps could allow patients to customize the platform, including the ability to edit information and select which aspects of their lives they wish to have tracked (55). This approach allows patients to choose the level of involvement they want the app to have in their care.

DHI could also provide patients with the option of attending clinics virtually whilst taking away issues associated with transportation. Online meeting platforms such as Microsoft Teams and Zoom may allow healthcare organisations to facilitate this (56). An RCT involving 200 patients exploring short-term medical care of ACS following PCI found that DHI increased medication adherence compared to standard care (56).

In a nonrandomized controlled trial involving 1064 patients, participants were given a mobile app, a smartwatch, and a blood pressure monitor (57). The authors found that DHI participants had a lower risk of all-cause unplanned 30-day readmissions than patients in the standard care group.

In addition to the health benefits to the patient, the implementation of DHI offers economic advantages to primary care and hospital systems. DHIs can enable hospitals to deliver treatment more cost-effectively at the population level. It has been previously suggested that DHIs are likely to be more effective when accompanied by human support (58). However, while integrating human factors could enhance the effectiveness of these interventions, the additional staffing required may result in increased costs (59) (41).

DHI may also play a role in preventing unnecessary invasive procedures. A study on coronary angiograms demonstrated that an ML model outperformed existing models in

predicting obstructive CAD, which has significant safety implications for patients by potentially avoiding complications associated with these procedures (60). However, before such models can be adapted for wider clinical practice, they must be trained using local data (60). This localization process tailors the ML model's output to the specific population, enhancing its accuracy and relevance in different clinical settings.

Physical activity monitoring devices can be integrated with mobile applications and are frequently utilized in commercial products like the Apple Watch and Fitbit. A systematic review of DHI found that DHI-encouraging PA could be used in medicine to promote PA in patients with chronic conditions. However, educating patients about potential adverse events is crucial, as they may be unaware of these risks (61). In a systematic review of 140 articles, DHIs, such as apps, telephone calls and text messages, were used in 56 RCTs, and 22 RCTs incorporated a DHI combined with a device such as a PA monitoring device or Bluetooth-enabled pulse oximeter (61). It also found that end-of-intervention effects favoured DHI for subjectively measured health-related quality of life with an effect size (standardized mean difference) of 0.18 (95% CI 0.07-0.29). The articles included in the review had varying levels of bias, with 6% of the studies classified as low risk of bias and 26% having a high risk (61).

Remote monitoring of patients is another valuable benefit of DHI. Allowing parameters such as blood pressure to be monitored remotely reduces the need for frequent clinic visits. This can lead to more consistent blood pressure readings and enhance the effectiveness of management strategies (62). Wearable devices could also detect arrhythmias such as atrial fibrillation, which could result in the early detection of these conditions (63). A systematic review of mobile apps in cardiology found that mobile technology could be used to monitor and analyse patient data remotely and may employ wearable devices and artificial intelligence (AI) (64).

### 1.3.2 Challenges and Limitations of Digital Health Interventions

DHI has several limitations that may affect its application in clinical practice. Despite the rapid development and adaptation of DHIs, their widespread use in clinical settings remains relatively new.

One of the significant concerns of DHI is the lack of evidence to support their effectiveness and safety (65). Several studies have investigated the efficacy of DHI (66). However, many of these studies are characterized by short follow-up periods or methodological limitations. Consequently, further research is necessary to determine the effectiveness of DHI more accurately.

A person's digital health literacy will also impact their ability to use apps and other DHI (55). This may be a particular concern for the elderly population, especially if they lack previous experience using mobile apps (55). Designing apps with certain features, such as a simple navigation system, may help elderly patients use apps more effectively (67). Operating systems like Android and iOS have established guidelines and recommendations to enhance mobile app usability (68). Adhering to these guidelines can improve the usability of a mobile app. Additionally, conducting usability testing before the app's release to patients and the broader population may further improve its usability (68).

Safety is another concern associated with DHI. As far as we are aware, currently, there are no set guidelines or a certification process to ensure that health-related apps are safe. This is an issue for the patients and all parties involved, including healthcare professionals and software developers (68). Apps that malfunction or, when developed poorly, may result in adverse events to the patient. The app may also give a user the wrong impression that it is a substitute for professional help when it is not (68). Therefore, patients must be informed of the benefits and risks of using any given DHI. Safety measures need to be implemented when things go wrong, and they should be advised on how to seek help when needed.

Data storage and retrieval is an essential aspect of the functioning of a mobile app. This inevitably could pose problems in healthcare apps as the app may store sensitive patient data either within the device itself or on cloud storage. Therefore, data privacy and confidentiality are vital considerations in the development of DHI (68). Several factors need to be taken into account within the domain of privacy. When signing up for a DHI, patients must be informed of the terms and conditions, including a privacy statement. They should also be informed which of their data will be stored. Confidential user data must be handled carefully, and users should have control over managing their data (68).

Developing an app that complies with relevant guidelines is a substantial undertaking. However, ongoing maintenance may require significant work and commitment even after development. Operating systems such as iOS and Android frequently update their platforms, which can render existing apps incompatible, necessitating updates to maintain functionality. These updates may alter the app's user interface or functionality, potentially requiring patients to undergo further training or seek technical support to continue using the app effectively (68).

It is important to anticipate any problems that may arise during an app's usage and implement any necessary measures to minimize these.

### 1.3.3 Physical Activity Monitoring Devices

Wearable devices are worn by over 10% of the population and include accelerometers (69). Accelerometers measure time-stamped accelerations of the body part to which the device is attached, in g's (gravitational force) in one to three orthogonal planes (70). Accelerometers may be worn on different body parts, including the wrist, the hip, the chest and the thigh (71). Over recent years, the usage of wrist-worn accelerometers in research has increased as they are more convenient for the patient (71).

A systematic review of wearable physical activity monitoring (PAM) devices found that, when used alongside exercise prescriptions or advice, these devices improved cardiorespiratory fitness compared to when PAM devices were not used (72). The authors also found that PAM devices did not result in any adverse cardiac events and improved participants' step count and psychological well-being (72). The review also found that using a PAM device did not impact dropout rates from the programme compared to situations where no device was used. When dropouts occurred, common reasons included lack of motivation and other personal commitments (72).

Accelerometers are developed and supplied by various companies. One such provider is Actigraph. The accelerometer data from certain providers, such as Actigraph, is converted into summary counts, such as Activity Counts (ACs) within an epoch (e.g. ACs per minute) (73). An epoch is a predefined time interval during which raw acceleration data is aggregated

or summarized for analysis (71). One of the advantages of ACs is that AC files take up less storage on a device compared to acceleration data (74). However, it could be challenging to compare ACs across different suppliers of accelerometers compared to raw acceleration data (74). The storage issue is becoming less significant as the storage capacity of new devices continues to increase (71).

Furthermore, consumer wearable devices such as Apple Watch, Fitbit, and Garmin are becoming increasingly popular devices that can measure PA (75). A study evaluating the reliability and validity of raw accelerometer data from Apple, Garmin and Fitbit found that these devices were reliable, and estimates of raw acceleration data were similar to the research-grade device Actigraph, except for Garmin (75). Actigraph develops several types of accelerometers. The Actigraph CentrePoint Insight Watch device is shown in Figure 1.2.




*Figure 1.2 Actigraph CentrePoint Insight Watch*

Accelerometer data from PAM devices can be classified into summaries such as moderate-to-vigorous physical activity (MVPA) minutes, light physical activity (LPA) minutes, and sedentary behaviour (76). This classification can be performed using different algorithms that determine the cut-off points, including the Freedson vector magnitude (VM3) algorithm and the Hildebrand algorithm (76, 77). Despite the Freedson algorithm being validated primarily for healthy adult populations, it continues to be widely used in research (76). Furthermore, the Freedson algorithm has only been validated when the PAM devices are worn on the hip (76).

One of the issues associated with processing accelerometer data is that most algorithms used to determine cut-off points have been validated primarily in healthy populations (78). As various studies may employ different devices, wear positions, and algorithms to establish these cut-off points, comparing results across studies can be challenging. ActiGraph accelerometers have been extensively used in cardiovascular research over the past 30 years, with participants commonly instructed to wear the device on the hip for seven days (78).

PAM devices often use ML algorithms to calculate ACs. In addition, AI and ML may be used in conjunction with DHI to augment their functionality even further.

## 1.4 Introduction to Artificial Intelligence and Machine Learning

Alan Turing first described using computers to simulate human intelligence and thinking in 1950 (79). In 1956, John McCarthy described AI as the "science and engineering of making intelligent machines" (80). AI first started as a simple set of ("if" and "else") rules that computers followed to make decisions (81). AI has grown over the years and now includes several subfields, such as machine learning (ML), deep learning (DL), and computer vision (81). Despite the early foundations of AI, its adoption in medicine has progressed relatively slowly. During these initial years, digital database systems such as the Medical Literature Analysis and Retrieval System (MEDLARS) and PubMed were developed, laying the groundwork for future advancements in AI within the medical field (81).

In the history of AI, most of the time period between the 1970s and 2000s was referred to as the "AI winter" (82). AI winter refers to a period in which there was reduced funding and interest in AI research (82). However, despite the general lack of interest during this period, pioneers in AI persisted in advancing the concept, contributing to its ongoing development (81). From 2000 to 2020, computer software and hardware became more and more sophisticated, paving the way for the growth of AI in medicine. Digitization of healthcare data contributed to this growth (81).

There are numerous benefits of AI. AI has the potential to benefit patients clinically by enabling the early diagnosis of medical conditions (83). Additionally, it could alleviate the

workload of clinicians, allowing them to concentrate on other aspects of care while tasks manageable by AI are automated (83). As the efficiency of AI improves, it is expected to yield cost-saving benefits for healthcare organizations (83). AI can generally identify meaningful patterns in data, including text, images, and videos (84). It can also be utilized to develop self-learning models adapting to new data (84).

A subset of AL is ML (85). Using a machine learning (ML) algorithm, a computer can be trained to perform a specified set of tasks without being explicitly programmed for each task. ML can be further divided into supervised learning, unsupervised learning, and reinforcement learning (Figure 1.3) (85). In supervised learning, a computer is trained using data that is labelled so that when presented with new data, it can perform a set task. In contrast, in unsupervised learning, a computer uses data that is unlabelled and attempts to identify any hidden patterns in the data. Examples of supervised learning include regression and classification (86). Semi-supervised learning involves a combination of both supervised and unsupervised learning.

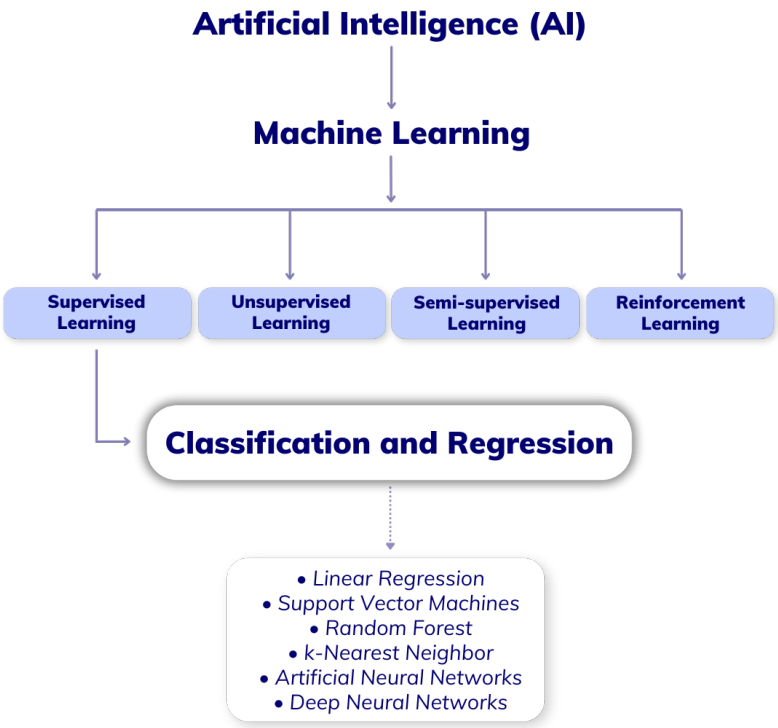



*Figure 1.3 Artificial Intelligence Classifications*

Reinforcement learning (RL) operates by interacting with an environment through a trial-and-error approach. In this method, the system learns by receiving rewards for productive or positive behaviour and penalties for unproductive or harmful behaviour (85). In RL, the agent interacts with the environment to achieve a specific goal. The agent's objective is to learn an approach to maximise rewards over time. An example of RL is a computer chess game in which the agent learns through repeated play with a human, often achieving better results than a human over time.

In regression learning, the goal is to predict a continuous output variable (the dependent variable) based on one or more input variables (independent variables) (85). An example of this could be predicting the step count a person is likely to do based on their characteristics and performance over the last few weeks. In contrast, classification learning aims to predict a discrete label or category rather than a continuous variable (85). For instance, classification is employed by various email providers to categorize emails as either "spam" or "not spam".

Linear regression is one of the simplest forms of regression learning (87). Linear regression is founded on the principle that the relationship between the input and output variables is linear, meaning that a unit change in the input variable leads to a proportional and constant change in the output variable (87). Multiple regression is a more complex form of linear regression in which numerous input variables are used to predict one output variable.

Other types of supervised learning include XGBoost and K Nearest Neighbour (88). XGBoost is short for Extreme Gradient Boosting and can be used for both classification and regression tasks. XGBoost is capable of solving complex problems faster and is also scalable if the complexity of the problem were to increase (88). XGBoost has been used in medical research for tasks such as the prediction of sepsis and for creating risk prediction models for oesophageal cancer (89, 90).

A systematic review of the use of AI in CR concluded that AI has significant potential for the early detection of cardiac events and the home-based monitoring of patients (39).

### 1.4.1 Challenges of Using AI in Medicine

One of the key aspects in the development of an AI model is the training process. Training an AI model requires data that is relevant to answering a given question or performing a certain task. A poorly trained model will yield poor results, and therefore, it is important to have enough high-quality data for the model to learn from. Additionally, it is important that the training data accurately represent the population concerned. A model that is exposed to completely unrelated data may not yield a high-quality output.

Obtaining a training dataset in healthcare can prove to be a significant challenge. Many factors need to be taken into account, among which data privacy is an important consideration (91). Supervised ML requires labelled training data. As most of the available data isn't already labelled, the training dataset will need to be manually labelled. This may require the assistance of several personnel. Due to issues surrounding data privacy, sharing confidential patient data may not be possible (91). Funding this extra labour may be another challenge.

Once a training dataset is obtained, the ethical use of this data is crucial. If a dataset contains patient data, it is important to respect the consent given by the patients, which may limit the use of their data only for a particular purpose (92).

The source of a dataset is also very relevant. Obtaining a single dataset from a single source could introduce single-source bias and may not truly represent the target population (91). For example, a dataset from a single hospital may have data that is representative of that region and may not be representative of another region or country.

Another important aspect of an ML algorithm is being able to explain how the algorithm arrived at a given prediction. Many AI algorithms that are currently used to solve problems work as uninterpretable "black boxes" (91).

AI and ML are becoming increasingly commonplace and have widespread applications. AI, especially when used in healthcare, may be responsible for making medical decisions. As a result, accountability will become more and more important. Furthermore, as the output of an

ML model depends on the input data, regulatory bodies may require testing on human factors before the model can be used in practice (93).

Despite the numerous challenges, AI is becoming increasingly more and more common in healthcare and other areas of life.

## 1.5 Thesis Motivation and Hypothesis

CR services experienced significant strain during the COVID-19 pandemic. Due to staffing shortages, several CR programmes experienced disruption, resulting in patients being unable to access its services. Even when operating normally, low uptake of CR continues to be a problem worldwide due to barriers such as access to transport. Therefore, a home-based CR programme may make it more accessible to patients. Furthermore, if the exercise prescription process can be automated using AI, it may reduce the pressures on CR services, potentially reducing waiting times and improving uptake. This will also keep with the long-term NHS plan of making services digital over the next ten years. However, before a home-based CR programme can be adapted on a national level, the effectiveness of such a programme needs to be evaluated ideally with a multicentre RCT. Such a study could be a massive undertaking requiring significant time and funding. Therefore, assessing the feasibility of conducting a large-scale RCT following the successful development of the technology required to facilitate a home-based CR programme is important.

This thesis hypothesizes that it is feasible to conduct an RCT to assess the effectiveness of a home-based CR programme employing AI to prescribe personalised exercises for patients.

## 1.6 Aims of the Thesis

This research comprises three interconnected studies, each building upon the findings of the previous:

- **Study 1**: This initial phase focuses on developing and evaluating a comprehensive technological tool for home-based CR. It includes the development of a mobile app, a web portal, and an AI model capable of prescribing personalized exercises. The functionality and user experience are then tested on healthy hospital staff volunteers. (Chapters 3 and 4)

- **Study 2**: Building on the outcomes of Study 1, this phase involves usability testing of the app and web portal on a small cohort of patients who are post-ACS or cardiac surgery. (Chapter 5)

- **Study 3**: The final phase of this research involves a feasibility randomized controlled trial (RCT). This study is designed to evaluate the feasibility of conducting a large-scale RCT in the future. This feasibility assessment will provide important data on recruitment, retention, and implementation challenges, informing the design and execution of a potential subsequent large-scale clinical trial. (Chapter 6 and 7)

All the above studies will involve both quantitative and qualitative assessments.

# CHAPTER 2

# 2. Approaches to Mobile Application-based Cardiac Rehabilitation: A Systematic Review

## Key Learning Points from this Chapter

- This systematic review aimed to explore the various approaches mobile applications adopt to facilitate home-based CR.
- Home-based CR programmes frequently employed goal setting and the use of physical activity monitoring devices.

- Home-based CR programmes can overcome key barriers to traditional CR, including transportation difficulties and scheduling conflicts.

- None of the studies in this review described the use of AI or ML to automate exercise prescription, representing a significant research gap.

## 2.1 Introduction

Cardiovascular disease is the leading cause of death worldwide, accounting for 32% (17.9 million) of all deaths in 2019 (94). Of these fatalities, 85% were attributable to myocardial infarction and stroke (94). Cardiac rehabilitation is a multifaceted intervention encompassing patient education, risk factor modification, and physical activity (95). European Society of Cardiology guidelines recommend that all patients with acute coronary syndrome (ACS) should be offered cardiac rehabilitation (96). In the UK, the National Institute for Health and Care Excellence (97) recommend that every patient, regardless of age, should be offered cardiac rehabilitation with an exercise component following ACS to start within 10 days of discharge from the hospital. This should be offered at various times and locations, including at the person's home (97).

For patients who are unable to attend hospital-based rehabilitation (for example, due to transportation difficulties or concerns about hospital-acquired infections), home-based rehabilitation is a viable alternative (98). The Heart Manual is one of the most widely used programs in the UK. As part of this programme, patients receive written materials and a compact disc containing information about cardiac rehabilitation, including exercise instructions. A healthcare professional may also visit patients in their homes and provide telephone support. This approach has been demonstrated to be as effective as hospital-based programs (95).

A systematic review of smartphone apps for improving physical function capacity in patients referred for CR identified several strategies that an app might employ, such as physical activity monitoring, including the use of physical activity monitoring devices, goal setting, diet and medication support, and the use of motivational messages (99). This review also evaluated whether an article assessed adherence or feasibility. However, only six articles were included in this systematic review.

An international survey found that almost half of all cardiac rehabilitation programs were suspended during the COVID-19 pandemic but that many centres swiftly adopted technology-enabled programmes within 19 days of the pandemic declaration (100). This

transition aligns with the ambition of the NHS to enhance access to digitally enabled care (101). Mobile apps may employ diverse strategies such as goal setting, physical activity tracking and motivational messages to elevate the physical activity levels of participants (99). Artificial Intelligence (AI) may be used to assist with goal setting in mobile applications (102). Furthermore, the inclusion of a mobile app in cardiac rehabilitation is associated with enhanced participation rates (103). However, the relative effectiveness of these strategies remains unclear. Therefore, this systematic review aims to identify and summarise the techniques used by mobile application-based cardiac rehabilitation programmes.

## 2.2 Methods

This systematic review is reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) recommendations (104).

### 2.2.1 Eligibility Criteria

Studies that were published in English were eligible if they assessed a cardiac rehabilitation programme administered to patients solely through a mobile app. Review papers, commentaries, correspondence, and study protocols were excluded. Articles discussing the creation of a cardiac rehabilitation programme or mobile app but did not include testing with patients were excluded from this review. The review specifically focused on evaluating the effects of various interventions on participants. Studies that included hybrid programs in which patients participated in both hospital-based and home rehabilitation were excluded due to the difficulty of attributing observed effects to either the home or hospital programme.

### 2.2.2 Information Sources

We searched Embase, Medline and CINAHL from their inception to the 15$^{th}$ of May 2024 using the keywords: app AND cardiac AND (rehabilitation OR telerehabilitation). The detailed search strategy is in Appendix A.

### 2.2.3 Study selection

Two independent reviewers screened titles and abstracts for potentially eligible studies and assessed full-text articles against the eligibility criteria. Disagreements were resolved through consensus.

### 2.2.4 Data collection and variables

Data from the included articles were extracted using a *pro forma* that included the participant demographics, intervention duration, outcomes, number of participants, study design, strategies employed by the programme, country where the study was conducted, and publication year. We extracted whether an intervention included a web portal and whether participants received phone or video calls as part of the intervention. Additionally, we determined whether participants' mental health and quality of life were evaluated. The use of a System Usability Scale (SUS) or a qualitative component was also assessed.

### 2.2.5 Risk of bias

The risk of bias (ROB) was assessed for each article, taking into consideration the study methodology. For randomized controlled trials (RCTs), the Cochrane Collaboration ROB tool was used. Nonrandomized studies were assessed using the Risk of Bias in Non-Randomized Studies of Interventions tool (ROBINS I) and the Newcastle-Ottawa scale. Newcastle-Ottawa scale results were converted to the Agency for Healthcare Research and Quality (AHRQ) rating.

### 2.2.6 Synthesis methods

We used descriptive statistics to summarise the study results and present a narrative synthesis of the included articles. Study outcomes were presented as mean with standard deviation (SD) or median with interquartile range where available.

## 2.3 Results

### 2.3.1 Study selection

Of 310 records identified by the search, 23 were included in the review (103, 105-126) (Figure 2.1).

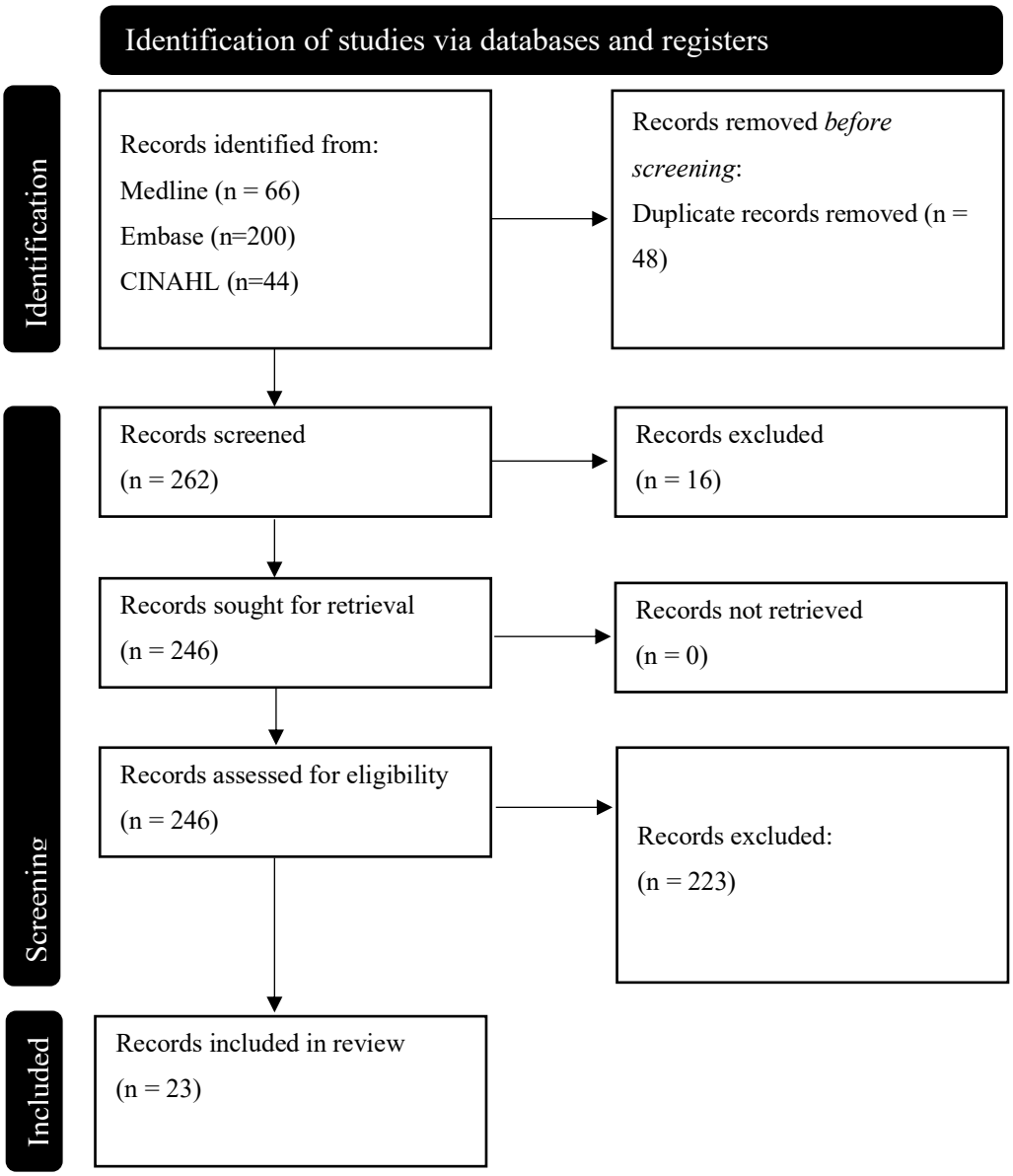



*Figure 2.1PRISMA Flow Diagram of the study selection process*

### 2.3.2 Study characteristics

Nine RCTs (112-114, 118-121, 123, 124), seven single-arm studies (106, 109, 110, 115, 122, 125, 126), one observational study with usability testing (105), one pre-test post-test study (103), one case-control study (107), one non-randomised controlled study (111), one qualitative study (117), one study using semi-structured surveys with usability testing (116) and one mixed-methods study (108) were included in the review, with a total of 1811 participants. Four studies (103, 123, 124, 126) were conducted in Australia, five (105, 106, 109, 111, 125) in the United States, twelve (108, 110, 112-115, 117-122) in Asia and two (107, 116) in Europe (Table 2.1).

*Table 2.1 Summary of included studies*

| Study | Number of participants | Average age of participants | Included Diagnoses | Country | Study Design | Intervention duration | Outcome measures |
|---|---|---|---|---|---|---|---|
| M Varnfield, 2014 (124) | 120 | 55.6* | Post MI | Australia | RCT | 6 weeks | -Uptake, adherence and completion of the programme<br>-Modifiable lifestyle factors (including PA), including 6MWT<br>-Biomedical risk factors (including blood pressure)<br>-Health-related QOL |
| A Beatty, 2018 (105) | 13 | 63* | CABG, PCI, Stable angina, HF | US | Observational study | Not stated | -Usability (SUS)<br>-Qualitative (semi-structured interviews) |
| N Freene, 2020 (126) | 20 | 54* | CABG, PCI | Australia | Pre-post design, Single-centre study | 6 weeks | -Feasibility outcomes including number of eligible participants and usability (Unified Theory of Acceptance and Use of Technology 2 questionnaire)<br>-Objectively measured Sedentary behaviour, MVPA, BMI, waist-to-hip |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | | | | ratio, blood pressure, 6-minute walk test, Quality of life, anxiety, and depression (HADS) |
| S Chiang, 2020 (118) | 50 | 60.0* | Cardiometabolic multimorbidity | Taiwan | RCT | 12 weeks | -Physical activity amounts<br>-Exercise capacity<br>-Health-related quality of life |
| A Sengupta, 2020 (125) | 10 | 64.4* | CHD, MI, HF, PCI, CABG | US | Single-group pre-post design | 12 weeks | -Usability (SUS)<br>-Waist circumference<br>-Depressive symptoms<br>-Dietary self-efficacy<br>-Exercise self-efficacy |
| A Harzand, 2018 (106) | 18 | 65* | CHD | US | Single-arm feasibility study | 12 weeks | -Feasibility and acceptability<br>-Blood pressure, functional capacity (symptom-limited exercise treadmill test or 6MWT)<br>-Safety (major adverse outcomes) |
| J Choi, 2021 (108) | 8 | Not stated | PCI | Korea | Patient focus group | 4 weeks | -Qualitative (Focus group interviews)<br>-Readability and usefulness (Likert scale) |
| E Ding, 2021 (109) | 18 | 58* | Acute MI | US | Single arm study | 12 weeks | -Time spent wearing a health watch<br>-Percentage of exercise goals completed<br>-Usability (SUS)<br>-Quality of life<br>-Counselling session attendance |
| T Liu, 2022 (112) | 60 | 53.27* | HF | China | RCT | 12 weeks | -6MWT<br>-MLHFQ Score<br>-Cardiac function index examination<br>-Compliance with exercise prescriptions |
| J Rivers, 2022 (103) | 204 | 70* | Angioplasty | Australia | Pre-post design | 6 weeks | -Participation rates<br>-Hospital readmissions |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| V Hatch, 2022 (107) | 102 | 57 intervention arm; 62 usual care* | CABG, PCI, MI (medically managed) | UK | Cohort / case-control study | 12 weeks | -Moderate activity minutes<br>-Vigorous activity minutes.<br>-Total Activity Measure in Metabolic Equivalent of Task in minutes<br>-Blood pressure |
| Y Son, 2023 (110) | 26 | 62 + | HF | South Korea | Pre-test-post-test<br><br>Usability testing | 24 weeks | -eHealth literacy<br>-Disease knowledge<br>-Self-care behaviours |
| A Oehler, 2023 (111) | 171 | 60.0 intervention; 66.0 control* | ACS, Stable angina, PCI, CABG | USA | Prospective, patient-selected study | 12 weeks | -Cost analysis |
| K Patterson, 2024 (123) | 15 | 59* | CHD | Australia | RCT | 6 months | - Semi-structured interview |
| S Stamm-Balderjahn, 2023 (116) | 158 | 57.9* | Cardiovascular disease | Germany | Semi-standardized written survey | 5 months | -System usability scale |
| S Lao, 2022 (117) | 10 | Not stated | PCI | China | Semi-structured interviews | 3 months | Qualitative data about the usability of intervention |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| S Lao, 2023 (121) | 140 | 68 experimental; 70 control group + | CHD patients who underwent PCI | Macao | Single-blinded, 2-arm, RCT | 10 weeks | -C-HADS, 6MWT, IPAQ-C<br>-Pill count, C-CLASP<br>-CESEI-C & CDSEI-C<br>-Blood pressure, pulse, BMI, smoking status<br>-App utility and satisfaction |
| K Xia, 2023 (115) | 31 | 56.2* | CHD (including PCI and CABG) | China | Quasi-experimental design study (single group) | 12 weeks | -Feasibility (defined as the extent to which subjects actively participated in and maintained the program) |
| Z Saleh, 2023 (120) | 127 | 61* | HF | Jordan | Secondary analysis of RCT | 8 weeks | -Physical activity (average daily step counts per week) |
| Z Saleh, 2023 (113) | 132 | 60.8* | HF | Jordan | RCT | 8 weeks | -Step count<br>-Heart failure symptom burden<br>-Health-related quality of life |
| I Nabutovsky, 2020 (122) | 22 | 52.7* | CAD | Israel | Single-centre, single-arm study | 6 months | -Safety, feasibility, and adherence<br>-Change in exercise capacity (stress test) |
| I Nabutovsky, 2024 (114) | 50 | 57.7 intervention, 61.6 control* | IHD, ACS, PCI, Cardiac surgery, atrial arrhythmias | Israel | Randomized prospective study | 16 weeks | -Change in muscle endurance<br>-Functional capability changes<br>-Cardiorespiratory fitness<br>-Compliance and adherence<br>-Questionnaires defining mental and physical health |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | , chest pain | | | | |
| I Nabutovsky, 2023 (119) | 306 | 57.7* | CHD | Israel | Single group | 6 months | -Effectiveness of the programme<br>-Correlate the programme goals and first-month activity, with attaining programme goals during the last month |

Abbreviations:
MI: Myocardial Infarction; RCT: Randomized Controlled Trial; PA: Physical Activity; 6MWT: 6-Minute Walk Test; QOL: Quality of Life; CABG: Coronary Artery Bypass Grafting; PCI: Percutaneous Coronary Intervention; HF: Heart Failure; US: United States; SUS: System Usability Scale; MVPA: Moderate to Vigorous Physical Activity; BMI: Body Mass Index; HADS: Hospital Anxiety and Depression Scale; CHD: Coronary Heart Disease; ACS: Acute Coronary Syndrome; MLHFQ: Minnesota Living with Heart Failure Questionnaire; CESEI-C: Chinese Cardiac Exercise Self-Efficacy Instrument; CDSEI-C: Chinese Cardiac Diet Self-Efficacy Instrument; IPAQ-C: International Physical Activity Questionnaire-Chinese Version; C-CLASP: Chinese Version of the Cardiac Lifestyle Self-Efficacy Scale; CAD: Coronary Artery Disease; IHD: Ischemic Heart Disease.
*Mean + Median

The feasibility or usability of the intervention was assessed in 14 studies (table 2). Four studies (105, 109, 116, 125) used SUS for this. Adherence to the intervention was also assessed in 17 studies, and all the studies with data relating to adherence showed positive results (Table *2.2*).

*Table 2.2 Classification of Studies*

**1. Intervention included a physical activity component 2. The intervention included a dietary component 3. The intervention included a medication component 4. Physical activity monitoring device used 5. Intervention involved goal setting 6. The intervention involved a web portal 7. Participants received phone or video calls as part of intervention 8. Participants received motivational messages as part of intervention 9. The study assessed adherence to intervention 10. The study assessed participants' mental health 11. The study assessed participant quality of life 12. The study assessed usability or feasibility 13. The study used a system usability scale (SUS) to assess the usability of intervention 14. The study involved a qualitative component.**

| Study | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **M Varnfield, 2014 (124)** | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | ✓ |
| **A Beatty, 2018 (105)** | ✓ | ✓ | | | ✓ | | | | ✓ | ✓ | | ✓ | ✓ | ✓ |
| **N Freene, 2020 (126)** | ✓ | | | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| **S Chiang, 2020 (118)** | ✓ | | | | ✓ | ✓ | | | ✓ | ✓ | ✓ | | | |
| **A Sengupta, 2020 (125)** | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **A Harzand, 2018 (106)** | ✓ | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | | ✓ | | ✓ |
| **J Choi, 2021 (108)** | ✓ | ✓ | ✓ | | | | | ✓ | | ✓ | | ✓ | | ✓ |
| **E Ding, 2021 (109)** | ✓ | | | ✓ | ✓ | ✓ | ✓ | | ✓ | | ✓ | ✓ | ✓ | ✓ |
| **T Liu, 2022 (112)** | ✓ | | | ✓ | ✓ | | | | ✓ | ✓ | ✓ | | | |
| **J Rivers, 2022 (103)** | ✓ | | | | ✓ | ✓ | ✓ | ✓ | | | | | | ✓ |
| **V Hatch, 2022 (107)** | ✓ | | | ✓ | ✓ | ✓ | ✓ | | | ✓ | | | | ✓ |
| **Y Son, 2023 (110)** | ✓ | ✓ | ✓ | | ✓ | | | ✓ | | | | ✓ | | ✓ |
| **A Oehler, 2023 (111)** | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | | | | |
| **K Patterson, 2023 (123)** | ✓ | | | ✓ | ✓ | | | ✓ | | | | | | ✓ |
| **S Stamm-Balderjahn, 2023 (116)** | ✓ | | ✓ | | ✓ | | | ✓ | | | | ✓ | ✓ | ✓ |
| **S Lao, 2022 (117)** | ✓ | ✓ | ✓ | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ |
| **S Lao, 2023 (121)** | ✓ | ✓ | ✓ | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ |
| **K Xia, 2023 (115)** | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | |
| **Z Saleh, 2023 (120)** | ✓ | | | | ✓ | | | ✓ | | ✓ | | | | |
| **Z Saleh, 2023 (113)** | ✓ | | | | ✓ | | | ✓ | ✓ | ✓ | ✓ | ✓ | | |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **I Nabutovsky, 2020 (122)** | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| **I Nabutovsky, 2024 (114)** | ✓ | | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| **I Nabutovsky, 2023 (119)** | ✓ | | | ✓ | ✓ | | ✓ | ✓ | ✓ | | | | | |
| **Total number of studies** | 23 | 9 | 8 | 10 | 22 | 10 | 12 | 16 | 16 | 16 | 12 | 13 | 4 | 13 |

### 2.3.3 Risk of bias assessment

Studies analysed using the Newcastle-Ottawa quality assessment score were of fair or poor quality (Appendix B), primarily due to low compatibility scores. Studies analysed by the RoB 2 tool largely had a low level of concern for the risk of bias. Studies analysed by the RoB-I tool showed that the majority of studies were at a serious or moderate risk of bias overall. This was due to serious risks in two domains: bias due to confounding and bias due to selection of participants.

### 2.3.4 Results of studies

#### *Physical Activity Monitoring Devices*

Ten articles described the use of physical activity monitoring (PAM) devices. In a single-arm prospective study of 22 patients with established coronary artery disease, a smartwatch was used to measure the activity levels of the patients (122). Participants were instructed to wear the watch during all exercise sessions and then upload the data to a remote cloud. These data were then displayed to the patient through a mobile application. The exercise capacity was assessed using estimated maximal METS (metabolic equivalent) and pre- and post-exercise stress tests. The study concluded that tele-cardiac rehabilitation programs could improve patients' functional improvement as estimated METS increased from a mean of $10.6 \pm 0.5$ (SD) to $12.3 \pm 0.5$ ($p = 0.002$) following the six-month CR intervention. One of the limitations of this study was the small sample size.

In another study, at the baseline visit, patients received a health watch (provided by Philips Healthcare) and a tablet (109). Throughout the 12-week study period, patients wore the watch for a median of 61 out of 84 days (73%) and 12.7 hours per day. There was a mean weekly decrease in watch wear time of 3.6 minutes. Some participants noted inconsistencies in the system, particularly regarding including short and intermittent walks picked up by the health watch, which did not contribute to the total walking time. This aspect discouraged certain patients. However, overall, patients found the system highly usable, as indicated by a median score of 83 out of 100 on the SUS. This study had several limitations, including a small sample size and a low proportion of eligible screened patients.

PAM devices may be worn in different body locations. In a prospective feasibility cohort study to evaluate the feasibility of a mobile app (Vire) and web-based behaviour change programme by Freene et al., participants wore a triaxial accelerometer on their right hip during their waking hours for seven days (126). The device evaluated the participants' sedentary behaviour and physical activity levels, and the authors found that participants spent, on average, 11 to 12 hours per day in a seated position. Over 16 weeks, a medium effect size was observed (Cohen's d = 0.54) for reducing sedentary behaviour, measured in minutes per day. The study had several limitations. It was a single-centre study where most participants were men, limiting the generalizability of the results in cardiac rehabilitation settings.

A study conducted by Xia et al., aimed to evaluate the feasibility of a mobile app used to deliver a 12-week remote CR programme (115). As part of the intervention, patients were provided with a chest-worn heart rate belt (Recovery Plus Inc), which was utilized to monitor exercise frequency and progress. The belt guided the exercise sessions, issuing a voice reminder through the app if the target heart rate was not achieved, prompting participants to adjust the intensity of their exercise accordingly.

### *Goal Setting*

Researchers in a study involving 10 women examined goal setting using a smartphone app and a smartwatch (125). During the study, the participants were instructed to set walking goals for up to 60 minutes each. If participants had not achieved their goals, they were

presented with the number of minutes remaining to complete the goal when checking their progress. The study concluded that this intervention was both feasible and usable for women diagnosed with coronary heart disease (125).

In another pilot study with 18 acute myocardial infarction survivors, a CR nurse reviewed the patients' activity level data and set them weekly goals (109). The patients were contacted weekly to assess their progress and provide cardiac rehabilitation counselling. Activity level data were collected using a health watch, tracking the patients' heart rate. Participants utilized a tablet computer to monitor their progress towards achieving their exercise goals. The authors found that the participants wore the PAM device for a median of 12.7 (interquartile range 11.1 to 13.8) hours per day and completed a median of 86% of their goals.

In a feasibility study, 20 participants were instructed to wear a Fitbit Flex for 16 weeks. Automated goals were delivered to the patients via the device. Data gathered from this device and GPS data collected from another application were utilized to compute scores in three domains: physical activity, social opportunity, and variety. The physical activity component factored in the daily step count and the duration of physical activity. The information collected from these devices created a digital profile for each patient. Based on this profile, behavioural goals in the form of "Do's" were communicated to the patients, totalling 89 different Do's, prompting the participant to reduce the time spent sitting. The authors found that 73.7% (252/342) of the Do's were completed to the participants (126). Given that this was a single-cohort study, the small to medium reductions in sedentary behaviour might not be directly linked to the ToDo-CR behaviour change programme. These changes could have arisen from the cardiac rehabilitation programme or measurement reactivity.

None of the studies included in this review employed AI to prescribe exercises.

### *Diet and Medication*

Ten studies included in the systematic review featured a dietary component, while nine incorporated a medication component as part of the intervention. Varnfield et al. evaluated the effects of a smartphone-based CR programme compared to a traditional centre-based programme in post-MI patients (124). Each patient was given access to a health diary

(WellnessDiary, Nokia Research), enabling them to record daily health entries such as weight, blood pressure, and dietary habits. The authors observed significant improvements in dietary intake among participants in both the intervention and control groups.

A mixed-methods pilot study evaluating the preliminary effectiveness and usability of a mobile-phone-based intervention for patients with heart failure concluded that the app was effective in improving adherence to self-care behaviours (110). The effectiveness was measured by assessing the improvement in patients' disease knowledge using the eHealth literacy scale (127). Participants' median score increased from 7.0 (IQR,5.0 to 8.3) to 9.0 (IQR, 8.0 to 10.0) ($Z = 3.92$, $P < 0.001$) after the intervention. The app included a feature to remind participants to take their medication at a set time. It also reminded them of hospital follow-up visits. The study also included a qualitative component where, as part of the interviews, the patients stated that the app helped with their motivation towards self-care behaviours whilst increasing awareness.

### *Web portal for monitoring the patients*

A single-arm, non-randomized feasibility study of a home-based cardiac rehabilitation programme used an online dashboard to monitor the patients (106). Study participants were encouraged to perform 30 minutes of light to moderate-intensity exercise at least five times weekly. A cardiology physician assistant remotely monitored the data entered by patients into the mobile app via the web portal and developed personalised exercise plans for each patient. They also reviewed patient messages and symptom alerts generated through the app. The authors found that all 18 patients could access the app and, logged an exercise session at least once, and were active through the first four weeks of the CR programme. The study had several limitations, including the small sample size of 18 patients, the absence of a control group and the short follow-up period.

### *Phone calls or video consultations*

In 12 studies, participants received phone or video calls as part of the intervention. In a study by Oehler et al., patients could attend traditional CR classes or home-based CR. Patients received an initial video call and weekly calls thereafter (111). During the initial call, a care

manager worked with the patient to set health goals and create a care plan. Subsequent calls aimed to assess and coach the patient on risk factors. The study found that the home-based intervention cost less than the traditional programme, as the average 12-month saving per participant was $1,377.

A study evaluating the feasibility of a smartphone app employed a quasi-experimental design, recruiting 31 patients (115). Patients downloaded the R Plus Health App, which gave them personalised exercise prescriptions. Exercise videos were used to guide the patients in supplementing the prescriptions. As part of the intervention, patients received monthly follow-up phone calls to discuss their progress and questions answered. Following the intervention, participants cardio-respiratory endurance improved as peak $VO_2$ increased from 22.43 to 23.66 ml/kg/min (mean deviation 0.6, 95% CI 0.1 to 2.4, P=0.04). No adverse events were reported during the study period.

The effectiveness of a mobile app was assessed as part of an RCT that recruited 140 patients onto an app-based CR programme or a control group (121). The app (mCR) featured text messaging, remote monitoring, and self-monitoring. In this study, patients received a phone call in the fourth and ninth weeks to assess and encourage them to use the mobile app. Following the intervention, the authors observed a significant improvement (P = 0.046) in the participants' six-minute walk test (6MWT) distance.

### *Use of motivational messages and positive feedback*

Motivational messages and automatic reminders were sent to the participants by the rehabilitation team in a study involving 22 patients with coronary artery disease (122). Users were able to alter the programme's configurations in such a way that they had control over how many messages they received. The authors found that many factors were important for the programme's success, including personalised human contact with the participants and motivational messages. The study web portal allowed the rehabilitation team to follow up with patients using messages and educational content. Patient satisfaction with this programme was high (4.05 of 5). The participants showed a significant improvement in their exercise capacity, as measured by the change in estimated METs. Following the intervention, it increased from a mean of 10.6 ± 0.5 (SD) to 12.3 ± 0.5, p = 0.002.

In a study done in Brisbane, Australia, patients undergoing angiography who declined conventional cardiac rehabilitation were offered an app-based rehabilitation programme. Patients were shown how to download the app after an initial consultation with a cardiac nurse. When the patient first logged in to the app, they were shown a set of daily and weekly goals. The app sent participants activity reminders and motivational messages. The authors found that giving patients the option of an app-based cardiac rehabilitation programme improved participation from 21% to 63%, p<.001 (103).

## 2.4 Discussion

In this systematic review, we have summarised strategies currently used in app-based CR programmes. Across various studies, integrating PAM devices and mobile apps facilitated improved exercise capacity and reduced sedentary behaviour and demonstrated high usability and patient satisfaction. A limitation of several of the included studies was the small sample size.

PAM devices are utilized by over 10% of adults in general and are increasingly employed to facilitate exercise (72). These devices can measure parameters such as step count, sedentary time, and moderate to vigorous physical activity minutes. A recent systematic review found that in combination with exercise prescription or advice, PAM devices were associated with an improved change in peak oxygen uptake (VO2 peak) (mean difference 1.65 mL/kg/min; 95% confidence interval [0.64–2.66]; p = 0.001; I2 = 0%) (72). Furthermore, the review highlighted the absence of reported cardiac events related to exercise in the nine included studies and identified improvements in psychological effects and exercise intensity facilitated by PAM device usage (72). Psychological effects were measured using scales including the depression, anxiety, and stress scale (DASS21), psychological distress scale (Kessler 6) and Kessler 10 scores. 62% of the non-cardiac adverse events were predominantly musculoskeletal injuries. Before this study, no other reviews evaluated PAM devices' effects in a cardiac population. In this review, the authors found that CR programmes frequently employ PAM devices and goal setting. With the advancement of technology, mobile apps are becoming increasingly sophisticated, including integration with AI algorithms (128). There is

the potential for AI to help facilitate goal setting, reduce the workload of rehabilitation staff and allow more patients to enrol in CR programmes, in particular, those based within the participant's home.

There are several potential advantages to a home-based exercise programme, including greater flexibility for the patient and more privacy while participating in the programme. It may also make the programme more accessible for patients who cannot attend the hospital due to the lack of transport or fear of infection. Motivational messages are also often employed by remote CR programmes and be effective and useful for patients in improving cardiovascular risk factors (129). Using mobile apps, these messages can be easily delivered to the participants, who can view them on their mobile devices. However, disadvantages of a home-based CR programme may include less social support, fewer face-to-face interactions, and less engagement with the programme (130). It also poses potential safety concerns for high-risk patients as current studies have been underpowered to assess the risk of adverse events in this group of patients (130). However, most of the studies included in this review evaluated the feasibility and acceptability of the rehabilitation programme rather than focusing on its effectiveness. This may be because most mobile app-based rehabilitation programmes are still in the testing phase, and feasibility needs to be established before conducting large-scale, effectiveness randomised control trials.

New methods of delivering CR are continually evolving. This includes hybrid models, a combination of home and hospital-based rehabilitation, as an alternative option to hospital-based rehabilitation. This enables greater patient choice and uptake of the intervention (131).

To our knowledge, this is the first systematic review to summarise the different strategies mobile apps use to deliver cardiac rehabilitation programmes. We used a robust methodology but recognise that the review has some limitations, including our search strategy, particularly regarding the risk of missing studies due to narrow inclusion criteria and keyword selection. Most of the studies had small sample sizes, and several studies only examined the usability or feasibility of a programme. None of the studies evaluated how different strategies may correspond to the effectiveness of a programme or compared them. Due to the heterogeneity of the studies, which can be attributed to between-study differences in patient selection, study design, clinical setting, CR programme design and the variety of outcome measures used,

only a narrative review was possible and not a meta-analysis. Furthermore, among the studies, there were a variety of primary diagnoses the participants were rehabilitating from-including heart failure, coronary artery bypass grafting, percutaneous coronary interventions, and angina. These factors were not accounted for in the analyses, which could have introduced bias.

The design of some of the included studies could have been improved, and the risk of bias was reduced as some studies were at high risk of bias. For example, one study had a critical risk of bias due to confounding (103). This is due to significant differences in the age of males between groups. Although not accounted for in the analysis, the authors acknowledge the risk of biases in the study design, particularly with the lack of a control group. Studies with a serious risk of bias due to the selection of participants were primarily due to the intervention and outcome being related to the selection of participants. For example, Nabutovsky and colleagues acknowledge the risk of bias introduced to the study, with patients who are more comfortable engaging with technology-based interventions being enrolled and influencing the outcome (122). However, this did not detract from the study's goal, which was to assess the feasibility and safety of the intervention.

Future studies should address the current gap in evidence of how approaches such as goal setting or motivational messaging may impact the clinical effectiveness of a programme rather than simply the acceptability or feasibility.

## 2.5 Conclusion

New methods of delivering rehabilitation are continually emerging. This allows greater patient choice and may improve the uptake of CR. Mobile apps can help create personalised rehabilitation programmes using activity tracking and custom goal setting strategies. None of the studies included in this review described the use of AI for exercise prescription. Tailoring the programme to the individual may help increase participation and compliance. However, future trials, including those focusing on long-term follow-up data, are needed to assess each strategy's relative effectiveness in improving participants' physical activity levels.

# CHAPTER 3

# 3. Development of a Machine Learning Algorithm for Physical Activity Goal Prescription

## Key Learning Points from this Chapter

- This chapter discusses developing and evaluating a machine learning (ML) model to prescribe physical activity goals for patients as part of a home-based cardiac rehabilitation programme.

Development of a Machine Learning Algorithm for Physical Activity Goal Prescription

- A real-life dataset was employed to train several machine learning models, including linear regression, ridge regression, XGBoost, K-nearest neighbour and random forest regressor.

- Hyperparameter tuning was used to achieve the best model performance for XG Boost and other models.

- Several ML model evaluation metrics, including $R^2$ , assessed model performance.

- XGBoost was selected for exercise prescription as it performed well and can automatically handle missing values, has built-in regularisation (to help with overfitting), is computationally efficient and is interpretable as it provides multiple ways to evaluate feature importance.

# 3.1 Introduction

## 3.1.1 Artificial Intelligence and Machine Learning

Artificial intelligence (AI) is a computer programme's ability to perform activities that normally require human intelligence. AI is increasingly used in medicine to automate tasks. According to the WHO report (132) on “Ethics and Governance of Artificial Intelligence for Health”, AI is being considered to make decisions in radiology. However, these approaches are still new and aren’t being used routinely. As AI improves, it could enable healthcare professionals to make quicker and more accurate diagnoses. It could help automate tasks, giving doctors more time with their patients.

With the emergence of AI, some services have been shifted from the hospital to the patient's homes. These include remote monitoring systems, including video-observed therapy for tuberculosis patients and virtual assistants to help patients. Since the COVID-19 pandemic, the number of telemedicine providers has increased considerably. Among the various tools employing AI are “just-in-time adaptive interventions”. These can adapt to the patient's needs using sensors to monitor them. It may use data collected from the patients to notify healthcare professionals about any concerns. (132)

A component of AI is machine learning (ML), which involves computer programs learning from data. (133) ML achieves this by analysing the relationships within the data and building statistical models. ML can be further subcategorised into supervised and unsupervised learning. In supervised learning, the goal is to predict a known output, whereas in unsupervised learning, there are no set outputs to predict. Here, the goal is to find patterns within the data. Some examples of supervised ML include automated interpretation of an ECG or detection of a lung nodule from a chest X-ray. (133)

There are various algorithms within supervised learning. Random forest is an example of an algorithm commonly used, using decision trees to generate predictions. An algorithm uses the features or predictors presented within the dataset to generate a prediction. Some of these features may contribute greatly towards the outcome, whereas others may not influence it

very much. Including some features within the algorithm may even contribute negatively towards the predictions. The area of ML that deals with this component is feature selection (133).

### 3.1.2 Feature selection

When presented with a dataset, selecting the features or variables to contribute to the predictions is an important step (134). There are various methods which may be used for feature selection. These may be broadly categorised as filter, wrapper and embedded (135). In the filter method, features are selected based on their statistical properties, and statistical measures are used to score and rank them. The filter method works independently of any ML algorithm. Correlation coefficients, information gain, chi-squared tests and mutual information may be used to select features. The filter approach may be fast and scalable, independent of the classifier and reduce the risk of overfitting. However, independence from an ML model may sometimes result in eliminating potentially useful variables that could enhance the model's predictive performance (135). A multivariate filter method can detect feature interactions and may be preferred over a univariate approach, as it examines the relationships among multiple features rather than assessing each feature independently (135).

On the other hand, in the wrapper method, features are selected based on the performance of a specific ML model. The predictive ability of different subsets of features is evaluated, and features which do not contribute to the predictive performance are discarded, whilst those that do are retained (135). This approach may yield better results than the filter method, which can model feature dependencies and model interaction with the classifier. However, it is more prone to overfitting, especially if the dataset is small or has many features (135). Examples of the wrapper method include sequential forward and backwards selection and randomised hill climbing (135).

In the embedded approach, feature selection is done as part of the model training process, identifying the most relevant features while fitting the model at the same time. It models feature dependencies and interaction with the classifier and is faster than the wrapper method. However, it is slower than the filter methods, and selected features may be classifier-

dependent (135). Examples of this approach include Random Forest and Lasso (L1) or elastic net regression (135).

Selecting the most important features that positively contribute to the model performance is important, as many features can lead to long model training times and result in overfitting (135). No single feature selection method may be considered superior to the other, and the choice of approach may need to be decided on a case-by-case basis (135).

Recursive feature elimination (RFE) is one approach that may be employed to assist with feature selection. This concept involves iteratively creating models, ranking the importance of features and removing the least useful features until a certain number of features is reached (136). RFE has previously been used in healthcare research, such as in models used to predict patients with inflammatory bowel disease who may be at high risk of unplanned healthcare use and for detecting COVID-19 based on complete blood count (136, 137).

Recursive Feature Elimination with Cross-Validation (RFECV) incorporates cross-validation into the feature selection process. This approach analyses the performance by fitting the model multiple times with several subsets of data, thereby enabling us to examine how well the model performs with varying features (138). RFECV offers an additional layer of validation compared to standard RFE, ensuring the selected features perform well with unseen data (139).

### 3.1.3 Model evaluation and selection

Cross-validation is a statistical approach used in machine learning to evaluate the performance of a predictive model. It is particularly useful in instances where there is only a limited amount of training data, as it could assist in reducing the likelihood of overfitting and improving the model's ability to work with new data (140).

Cross-validation involves randomly dividing the data into several equally sized subsets and training the model multiple times using all but one subsets. Following each training process, the excluded subset tests or validates the model. The number of subsets may be adjusted based on the developer's preferences. However, it is commonly represented by k. Therefore,

in k-fold cross-validation, k-1 subsets are used to train the model, and one subset is used for testing and model evaluation (140).

Cross-validation may also help with hyperparameter tuning (141, 142). This process may involve several approaches, including grid search and random search. Grid search cross-validation examines all different combinations of hyperparameters, whereas random search only evaluates a random possible combination of hyperparameters to achieve the best model performance (143). Hyperparameter tuning by cross-validation has been utilised by previous healthcare studies, including for survival prediction of children undergoing hematopoietic stell cell transplantation (142).

When presented with a problem, it is important to determine the best ML model for the presented task, as some models may perform better than others. In a study focusing on diabetes, several ML models were tested to non-invasively screen for pre-diabetes in children and adolescents using a national database. This study looked at six machine learning models, including XG Boost, random forest, decision tree classifier and support vector machine (144). XG boost was the best-performing model with the highest 10-fold cross-validation score. This model could aid clinicians in diagnosing pre-diabetes early and advise patients to make any necessary lifestyle modifications to prevent the condition.

The random forest (RF) algorithm is an ensemble learning method that can be used for both classification and regression. The model functions by creating several decision trees during training and outputting the mode of the classes for classification or mean prediction for regression of the individual trees ( Figure 3.1). Training takes place independently across all decision trees, and the final prediction is generated by taking the outputs of all the trees into account (145). This approach allows the model to deal with complicated data and handle complex interactions among features in the dataset, which is particularly important for real-life data (146).

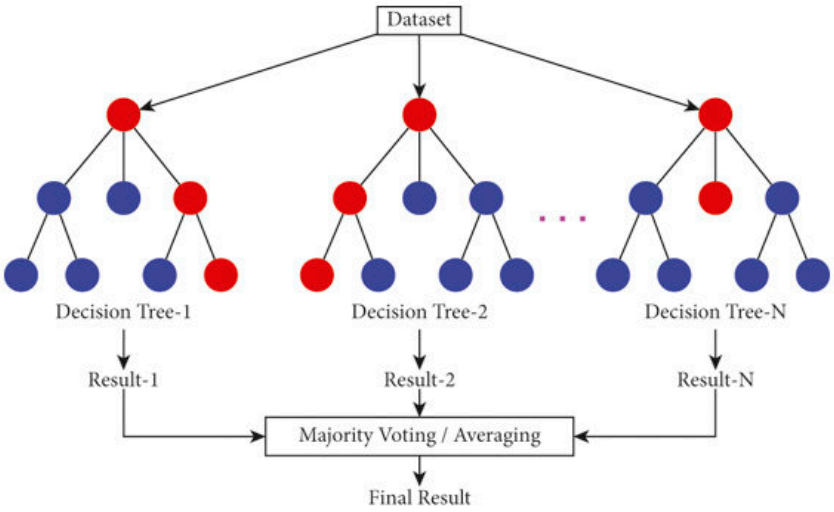



*Figure 3.1 Illustration of Random Forest Trees (147)*

Extreme Gradient Boosting (XGBoost) is based on the principle of gradient boosting. The model constructs decision trees to improve the accuracy of the predictions by minimising the errors made by previous models within the ensemble. XGBoost has been used in healthcare, for example, to predict drug-induced liver injury during tuberculosis treatment (143).

Various elements can affect the performance of a model, and in the case of a random forest model, the number of trees is an example of such a factor which can influence the predictions. These factors are referred to as hyperparameters, and hyperparameter tuning is an important component of model training, which can greatly impact its performance (144). The hyperparameters in random forest include the number of trees, tree depth and minimum sample parameters (148).

### 3.1.4 Research Gap

Traditionally, most CR programmes were offered to patients at the hospital or in the setting of a group session. However, over the last few years, centres worldwide started offering home-based CR programmes, some of which were delivered via mobile applications (149). Even in these cases, most programmes needed the input of a healthcare professional to prescribe physical activity goals or exercises (149).

If this process can be automated, hospitals can accommodate more patients in their CR programmes, potentially provide a more convenient form of rehabilitation, and reduce costs associated with delivering CR. To the best of our knowledge, currently, no CR programmes offer personalised exercise prescriptions to patients using AI.

This study aims to create an ML model that can generate exercise prescriptions for post-cardiac surgical and post-ACS patients, considering their age, height, weight, diagnosis, medication history, and past physical activity level data. In this study, we will train and evaluate several ML models. The ML model we create will be validated in the phase II of RECAP trial (ISRCTN: 97352737) after further refinement and training following phase I.

### 3.1.5 Primary Research Question

Is it feasible to develop a proof-of-concept machine learning framework for automated physical activity goal prescription in CR using retrospectively derived training data?

## 3.2 Methods

### 3.2.1 Objectives

1. To develop and compare multiple ML models for predicting weekly step count and MVPA minute goals for CR patients.
2. To identify key patient characteristics which have the highest impact on PA goal prescriptions
3. To determine the most suitable ML model with a high predictive capability, interpretability, and implementational ability in real-life practice

In this project, we aimed to assess the feasibility of deploying an ML model to an online server, feeding it data collected via accelerometers and retrieving PA goal prescriptions in real time.

The data used to train the models were obtained from the OPTICARE study (150).

### 3.2.2 OPTICARE Study

This randomised control trial recruited patients from Capri Cardiac Rehabilitation (an outpatient rehabilitation centre with several clinics in the Netherlands) between November 2011 and August 2014. Patients with an ACS diagnosis, over the age of 18 years, and proficient in Dutch were included. Any patients with severe physical and/or cognitive impairments that could impact their ability to take part in cardiac rehabilitation were excluded. Patients were either randomised to 1) 3 months of standard cardiac rehabilitation, 2) 3 months of standard CR with three pedometer-based face-to-face PA group counselling sessions followed by 9 months of aftercare with three general lifestyle face-to-face group counselling sessions or 3) 3 months of standard CR followed by 9 months of aftercare with five to six general lifestyle, telephonic counselling sessions.

An accelerometer recorded physical activity and sedentary behaviour at randomisation, 3 months, 12 months, and 18 months.

The dataset had 731 rows and 54 columns, corresponding to 731 patients. The data for these patients were recorded at four time points. T0 at randomisation, T1 at 3 months, T2 at 12 months and T3 at 18 months after randomisation.

The authors of the OPTICARE study concluded that adding accelerometer-based face-to-face counselling sessions focusing on improving levels of PA successfully increased the participants' daily step count and time spent in MVPA.

Table 3.1 shows the variables present in the OPTICARE dataset. The data included participants' demographic information, including sex and age, as well as their educational status, partner status and employment status. Education level was classified as low, intermediate and high. A participant was considered to have a low education level if their highest education level was primary school, intermediate if it was secondary school and high if they had completed a university degree. Partner status was classified as partnered (married,

registered partnership or living together) or unpartnered (single, divorced or widowed). Employment status was classified as employed (full-time or part-time paid employment) or unemployed (without a paid job or retired).

*Table 3.1 Physical activity columns and descriptors of the OPTICARE dataset*

| **Column** | **Description** |
|---|---|
| PPnumber | number participant |
| Randomization | Group allocation |
| Sex | Sex |
| Age | Age at baseline |
| Educational_status | Educational status at baseline |
| Partner_status | Partner at baseline |
| Employment_status | Employment at baseline |
| Treatment | Treatment before referral to rehabilitation |
| EMI | Cardiac history: Myocardial Infarction |
| EAP_1 | Cardiac history Angina Pectoris |
| EPTCA_1 | Cardiac history PCI |
| ECABG_1 | Cardiac history CABG |
| ECVA_TIA | Cardiac history Stroke/TIA |
| RiskFactor_FamiliyHistory | Risk factor family history |
| RiskFactor_DM | Risk factor diabetes |
| RiskFactor_Hypertension | Risk factor hypertension |
| RiskFactor_Dyslipidemia | Risk factor dyslipidemia |
| T0_weight_1 | Weight in kg |
| T0_length_1 | Height in cm |
| T0_BMI | BMI |
| RiskFactor_Overweight | Risk factor overweight |
| RiskFactor_Smoking | Risk factors smoking pre-ACS |
| AcetylsalicylicAcid | Medication use at baseline AcetylsalicylicAcid |
| CholesterolLoweringMed | Medication use at baseline CholesterolLoweringMed |
| ACEinhibitor | Medication use at baseline ACEinhibitor |
| CalciumBlocker | Medication use at baseline CalciumBlocker |
| BetaBlocker | Medication use at baseline BetaBlocker |
| Thienopyridine | Medication use at baseline Thienopyridine |
| OralAnticoagulant | Medication use at baseline OralAnticoagulant |
| Nitrate | Medication use at baseline Nitrate |
| Diuretic | Medication use at baseline Diuretic |

| | |
|---|---|
| Psychotropic | Medication use at baseline Psychotropic |
| Angiotensin2ReceptorBlocker | Medication use at baseline Angiotensin2ReceptorBlocker |
| T0_Validdays_AG | T0= baseline actigraph |
| T0_stepsday | Average number of steps per day T0 |
| T0_MVPA_min | Average minutes per day spent in MVPA T0 |
| T0_LPA_min | Average minutes per day spent in LPA T0 |
| T0_sed_min | Average minutes per day spent sedentary T0 |
| T1_Validdays_AG | T1=end of rehab (3 months) actigraph |
| T1_stepsday | Average number of steps per day T1 |
| T1_MVPA_min | Average minutes per day spent in MVPA T1 |
| T1_LPA_min | Average minutes per day spent in LPA T1 |
| T1_sed_min | Average minutes per day spent sedentary T1 |
| T2_Validdays_AG | T2= 1 year follow up (12 months after baseline) actigraph |
| T2_stepsday | Average number of steps per day T2 |
| T2_MVPA_min | Average minutes per day spent in MVPA T2 |
| T2_LPA_min | Average minutes per day spent in LPA T2 |
| T2_sed_min | Average minutes per day spent sedentary T2 |
| T3_Validdays_AG | T3= 1.5 year follow up (18 months after baseline) actigraph |
| T3_stepsday | Average number of steps per day T3 |
| T3_MVPA_min | Average minutes per day spent in MVPA T3 |
| T3_LPA_min | Average minutes per day spent in LPA T3 |
| T3_sed_min | Average minutes per day spent sedentary T3 |

The coefficient of determination, R squared ($R^2$), is a statistical measure which can describe the degree of variance (goodness-of-fit) in the dependent variable calculated based on the independent variables (151). R-squared is defined as the proportion of variance in the dependent variable that is explained by the explanatory (independent) variables or, equivalently, the proportional reduction in unexplained variance (151). In regression analysis, R squared measures how well the regression line approximates the data.

However, the value of the R-squared increases with the addition of further variables, regardless of whether or not they can successfully describe the degree of variance (152-154). The value of R-squared ranges from 0 to 1 (or 0% or 100%). A value of 0 indicates the model does not explain any variance, whereas 1 means the model perfectly predicts the dependent variable.

Unlike the R-squared value, which increases with the addition of variables irrespective of their relevance, the adjusted R-squared value penalises the model for including irrelevant variables (155). Adjusted R-squared can be used to assess the variability of each model. It is worth noting that a higher adjusted R-squared value could still be an indication of overfitting (156). However, adjusted R-squared values cannot accurately assess the performance of tree-based models as they were designed for linear regression models, where the relationship between independent and dependent variables is assumed to be linear.

Mean absolute error (MAE) is an important metric used to assess the performance of a regression ML model (157). It measures the average magnitude of the differences between the predicted value and the actual observed value. MAE is calculated by taking the average of absolute differences between the predictions and the actual values and hence provides a measure of prediction errors. A lower MAE values indicate better model performance. A perfect model has an MAE of zero.

Another widely used metric in evaluating regression models is the Root Mean Square Error (RMSE) (157). It measures the average magnitude of prediction errors by calculating the square root of the average squared differences between predicted and actual observed values. As RMSE squares errors before averaging, it penalises large errors more than smaller ones. It is also expressed in the same units as the dependent variable, hence making it easily interpretable. As errors are squared when calculating RMSE, it is more sensitive to outliers than MAE.

Explained variance is a statistical concept used in ML to quantify the proportion of variability in a dataset that is accounted for by a model. It measures the degree to which variation in the dependent variable is predictable from the independent variable(s). The values for this metric range from 0 to 1 (or 0% and 100%). A value that is close to 1 or 100% indicates a perfect model which has fully captured the underlying patterns in the dataset. Explained variance is often used in studies for evaluating ML models (158).

We used R-squared, MAE, and RMSE to evaluate the performance of the ML models.

### 3.2.3 Data pre-processing

*Data cleaning*

Following the analysis of the dataset, it was observed that some of the columns were not relevant to the task. These included columns that contained the patient identification number, randomisation status and physical activity level data at 12 months and 18 months following randomisation. The dataset also contained many missing values (Figure 3.2).

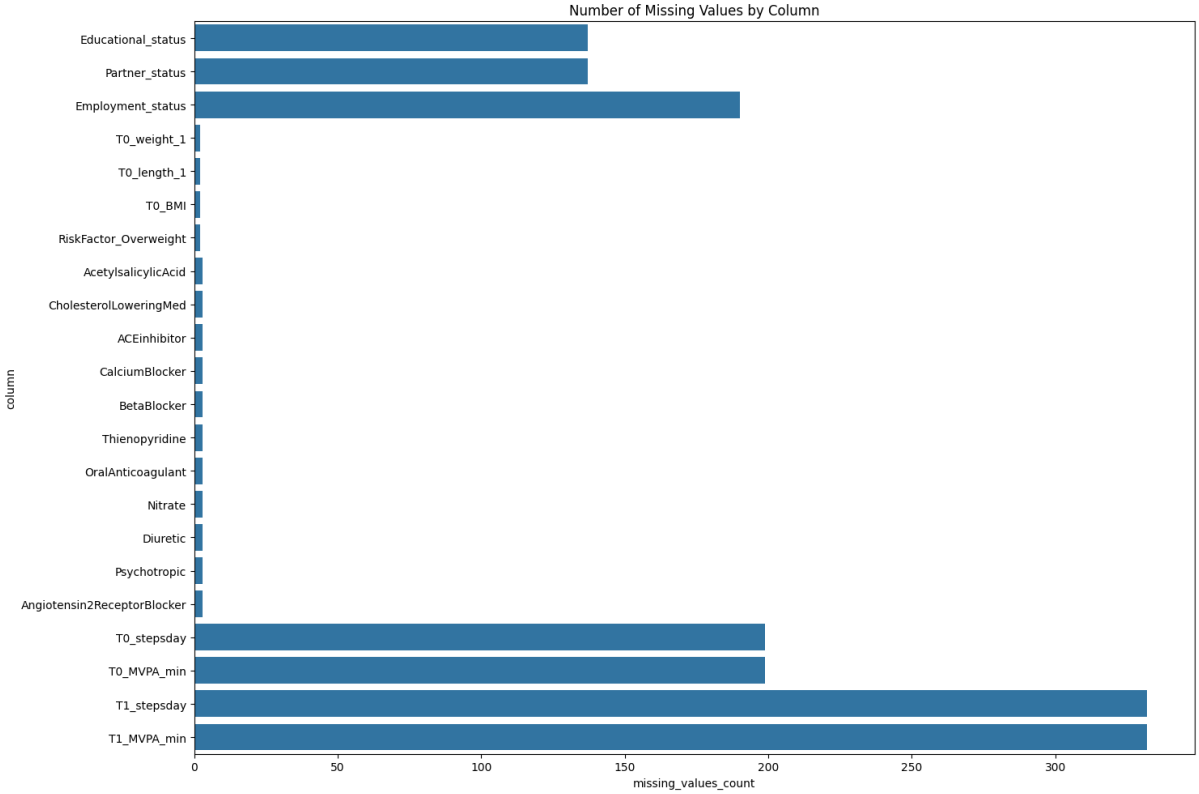



*Figure 3.2 Missing Values in the Original Opticare Dataset*

Missing values may be an issue in any large dataset. They may occur when the variable of interest is either not measured or not recorded. One approach to dealing with missing values is to replace them with the mean value of that variable using the data from subjects for which data is available (159). This approach may be referred to as “mean-value imputation”. One limitation of this method is that it reduces the variability in the data (159). In addition to this, it also ignores the multivariate relationships among various variables in the dataset.

A commonly used approach to dealing with missing values is multiple imputation. In this approach, missing values are replaced with multiple values. This creates multiple datasets in which the missing values have been replaced with several plausible values. Each dataset is then analysed separately, and the results are combined to create overall estimates (159). Missing values were addressed using the multiple imputation method. This is a commonly used approach in machine learning (159).

### *Feature Selection and Feature Engineering*

The goal of this algorithm was to prescribe exercises for patients primarily based on their past week's physical activity data. However, one of the limitations of the OPTICARE dataset was the fact that weekly activity level data weren't available for patients. Instead, activity level data was measured at baseline and at 3-, 12-, and 18 months following randomisation. To overcome this, we used the following formula:

- Step count prescription (goal, **X**) = T0 steps + (T1 steps – T0 steps)/13

- Moderate to vigorous physical activity (MVPA) minutes prescription (goal, **Y**) = T0 MVPA + (T1 MVPA – T0 MVPA)/13

(T0 measured at randomisation and T1 at 3 months)

In the above formula, the step count at 3 months (T1 steps) was the step count achieved by a participant measured over a week in the OPTICARE study, three months following randomisation. To get an approximate figure for the weekly increase in step count, we subtracted the step count at randomisation, measured over a week (T0) from the step count at three months (T1) and divided the value by 13 (approximately 13 weeks in a 3-month time frame). This value was then added to the step count at randomisation. The same approach was used to derive a value for the MVPA, as demonstrated by the second formula given above.

For the purpose of training the algorithm, the T0 physical activity data were taken to be the current week's physical activity levels and the values calculated using the above formulae (**X**

and **Y**) were taken to be the physical activity goals/prescriptions for the following week. Therefore, the algorithm aimed to predict the values **X** and **Y** (dependent variables) based on other variables (independent variables), including age, sex, education level and partner status.

As part of the RECAP clinical trial, patients' perceptions of their exercise prescriptions/goals will be collected using the BORG scale. However, the OPTICARE trial did not collect this information, and therefore, this data wasn't available. We used the following approach to create an extra column that would replicate the patient's perception.

1. Calculate the difference between T1 and T0 (T1– T0) for step count and MVPA
2. Divide the difference by T0 value and find the percentage increase
3. Compare the percentage increase and assign a perception value, as shown in Table 3.2.

*Table 3.2 Calculation of a perception score based on physical activity data*

| **Percentage Increase** | **Perception** | **Interpretation based on the BORG Scale** |
|---|---|---|
| > 10 | 0 | No exertion at all |
| >= 9 and < 10 | 1 | Extremely Light |
| >= 8 and < 9 | 2 | Slightly more effort |
| >= 7 and < 8 | 3 | Light exercise |
| >= 6 and < 7 | 4 | Moderate exercise |
| >= 5 and < 6 | 5 | Somewhat hard |
| >= 4 and < 5 | 6 | Heavy exercise |
| >= 3 and < 4 | 7 | Hard exercise |
| >= 2 and < 3 | 8 | Very hard |
| >= 1 and < 2 | 9 | Very severe |
| < 1 | 10 | Maximal effort |

Some features that were present in the original OPTICARE dataset but that wouldn't be captured in the RECAP trial study were omitted during the training and testing process. These features were T0_Validdays_AG, T1_Validdays_AG, T1_stepsday, T1_MVPA_min, T1_LPA_min, T1_sed_min, T2_Validdays_AG, T2_stepsday, T2_MVPA_min,

T2_LPA_min, T2_sed_min, T3_Validdays_AG, T3_stepsday, T3_MVPA_min, T3_LPA_min and T3_sed_min.

#### *Safety of Prescribed PA Goals*

To ensure the safety of the PA goals prescribed by the ML model, the software notified a clinician via the web portal if the prescribed goals exceeded 15% of the current week's PA levels. In this case, the new goals weren't displayed on the participant's mobile app until a clinician has approved it and deemed to be safe.

## 3.3 Results

### ML model training and evaluation

Data from the OPTICARE study was used to train several different machine learning models, including linear regression, k-nearest neighbours, random forest and XG Boost.

Figure 3.3 is a heatmap representing a correlation matrix exploring the relationship among the top predictors in the PA goal prediction models. In order to determine the top features, four different approaches were employed: XGBoost feature importance, which quantified each feature's contribution to the accuracy of predictions; mutual information, which captured non-linear relationships among features; absolute correlation coefficients, which provided a measure of linear association strength while RFECV performed iterative feature elimination to identify optimal features through cross-validation. A moderate positive correlation exists between perception and both steps (r=0.456) and MVPA minutes (r=0.445). The remaining features demonstrate minimal correlation with each other, with correlation coefficients predominantly being below 0.1. It is important to note that in our approach to feature engineering, perception was determined by the difference between T1 and T0 for both step count and MVPA. Therefore, inevitably, there will be a correlation between perception, step count, and MVPA.

Figure 3.4 illustrates how the number of features contributes to the $R^2$ score based on a XGBoost Regressor. The graph demonstrates that with just 5 features, the $R^2$ value reaches over 0.80 for both steps and mvpa goals. However, the addition of more features does not significantly affect this value beyond that. In fact, with 39 features, the $R^2$ reached 0.8766, and with only five features, it was 0.8832 for mvpa goals. For step goals, the $R^2$ value was 0.8481 with 39 features and with 10 features, it was 0.8548. Therefore, more features may have a negative effect on the predictive value.

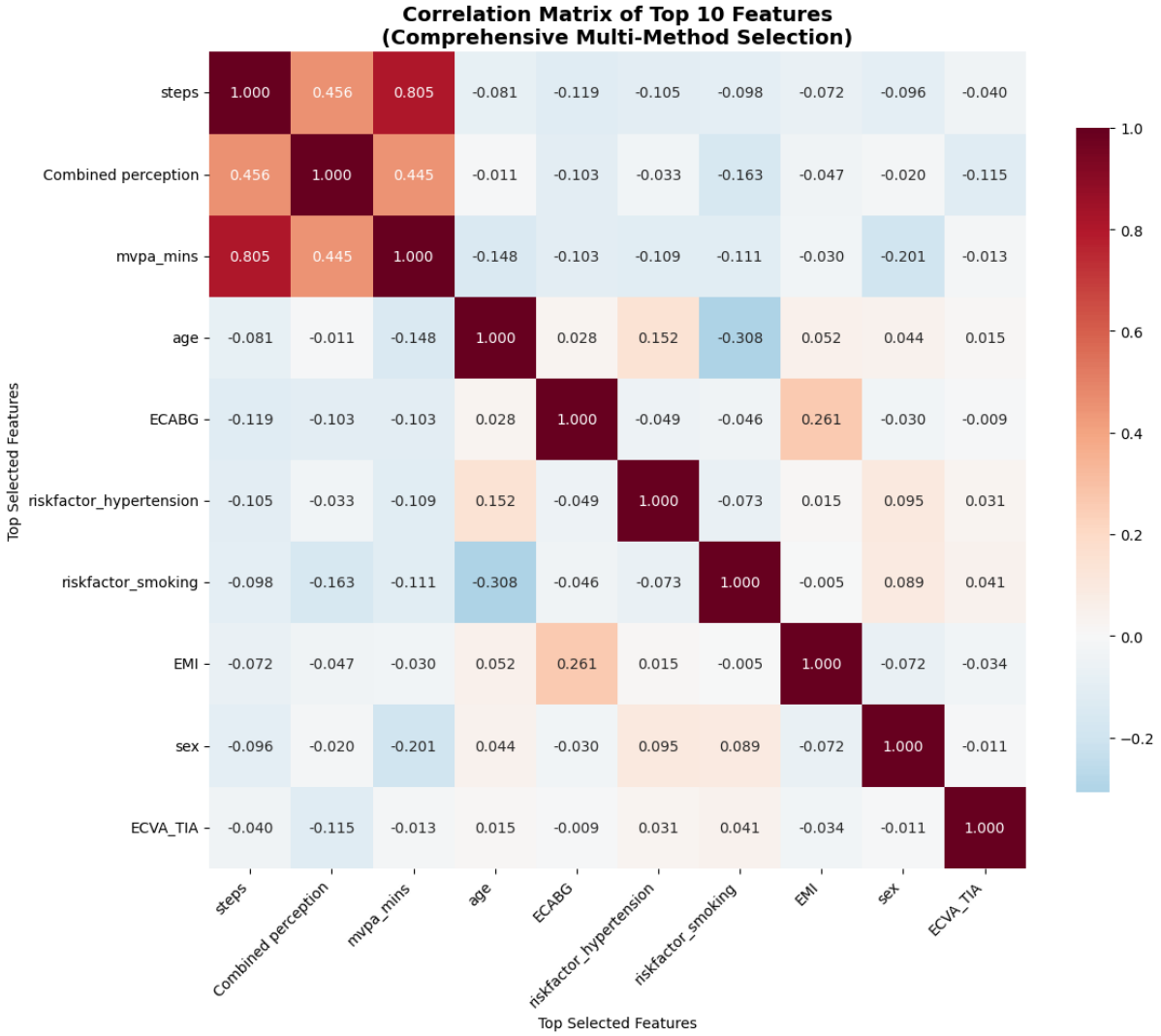



*Figure 3.3 Correlation Matrix for Top 10 Features*

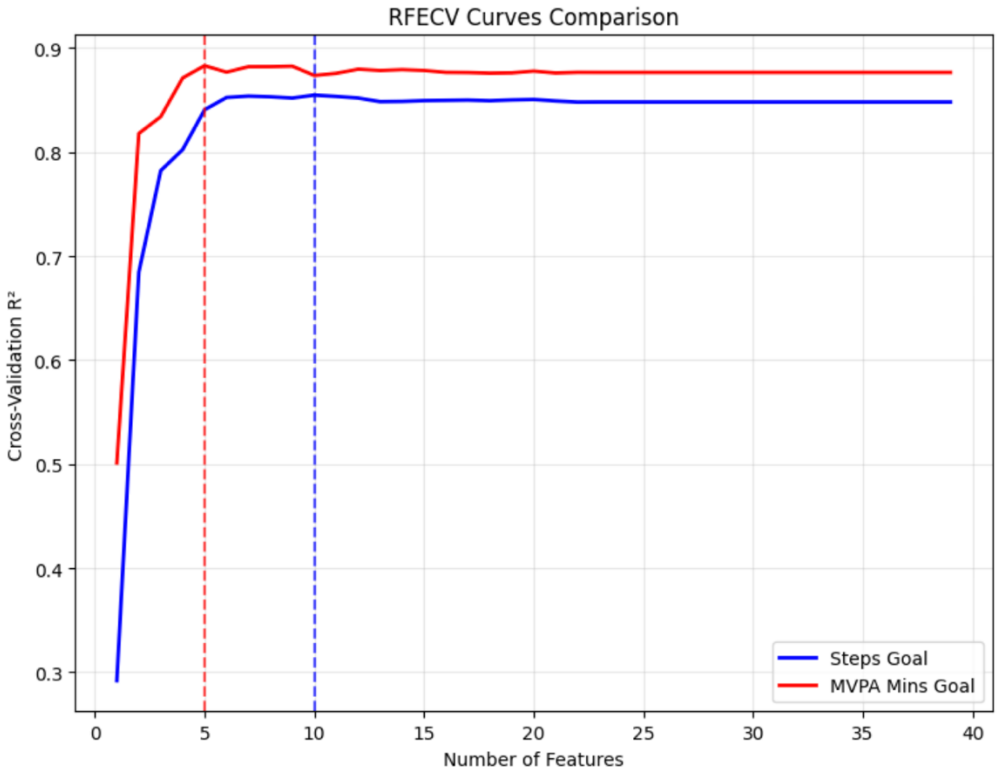



*Figure 3.4 Performance vs Number of Features determined using Recursive Feature Elimination with Cross-Validation (RFECV)*

*Table 3.3 Performance measures of the different ML models*

| Model | CV $R^2$ | CV RMSE | CV MAE |
|---|---|---|---|
| **Linear** | 0.5170 | 18.9 | 13.9 |
| **Ridge** | 0.5133 | 18.9 | 13.9 |
| **Lasso** | 0.5191 | 18.9 | 13.8 |
| **ElasticNet** | 0.5066 | 19.1 | 13.9 |
| **KNN** | 0.5565 | 18.1 | 14.4 |
| **MLP** | 0.8249 | 10.8 | 7.8 |
| **Extra Trees** | 0.8959 | 8.7 | 5.1 |
| **Random Forest** | 0.8852 | 9.2 | 4.5 |
| **Gradient Boosting** | 0.8500 | 10.5 | 5.8 |
| **XGBoost** | 0.8880 | 9.1 | 5.4 |

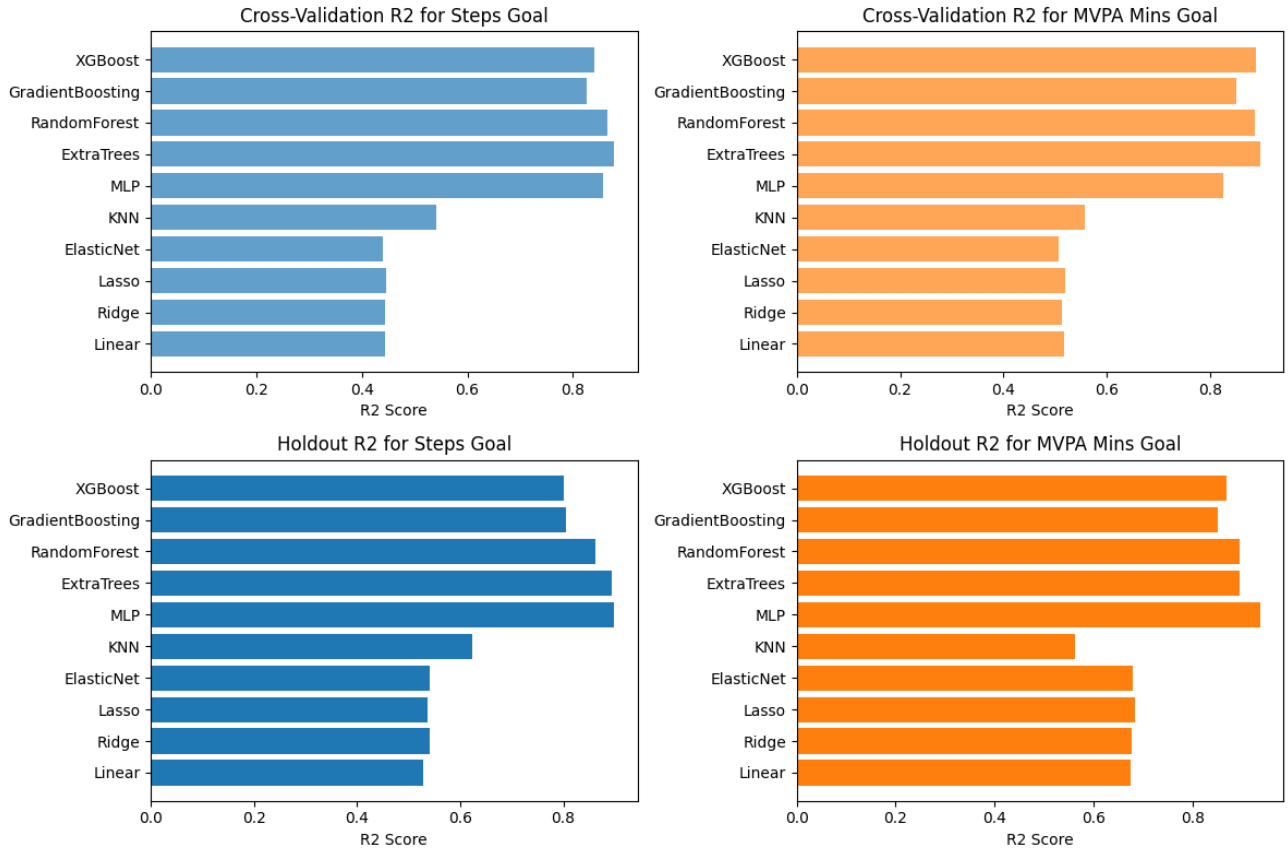



*Figure 3.5 Comparison of $R^2$ scores*

Table 3.3 and Figure 3.5 illustrate the performance of different models. Both XGBoost and Random Forest demonstrated high predictive accuracy, as reflected by the $R^2$ scores. Linear regression and Ridge regression demonstrated the lowest performance among models.

Grid Search Cross-Validation (GSCV) was used to tune hyperparameters to enhance the performance of the XGBoost model. This technique has been previously used to improve the performance of ML models (160, 161).

Several hyperparameters were tested, as shown in Table 3.4 for XGBoost.

*Table 3.4 Hyperparameter Tuning for XG Boost*

| Hyperparameter | Values | Optimal value |
|---|---|---|
| **max_depth** | 1, 2, 3, 4, 5 | 3 |
| **n_estimators** | 10, 15, 20, 25, 30, 35, 40, 50 | 40 |
| **learning_rate** | 0.01, 0.03, 0.05, 0.07, 0.09, 0.11, 0.13, 0.15, 0.17, 0.19, 0.2 | 0.17 |
| **min_child_weight** | 1, 3, 5, 7, 9 | 1 |
| **gamma** | 0, 0.1, 0.2, 0.3, 0.4, 0.5 | 0 |
| **subsample** | 0.6, 0.7, 0.8, 0.9, 1.0 | 0.8 |
| **colsample_bytree** | 0.6, 0.7, 0.8, 0.9, 1.0 | 0.9 |
| **reg_alpha** | 0, 0.001, 0.01, 0.1, 1.0 | 0.1 |
| **reg_lambda** | 0.1, 1.0, 10.0, 100.0 | 1 |

Figure 3.6 demonstrates the predictive capabilities of various features of the dataset for the XGBoost model. The step count is the most significant predictor, by a large margin, outperforming all other variables. Perception and mvpa minutes had the next highest predictive power.

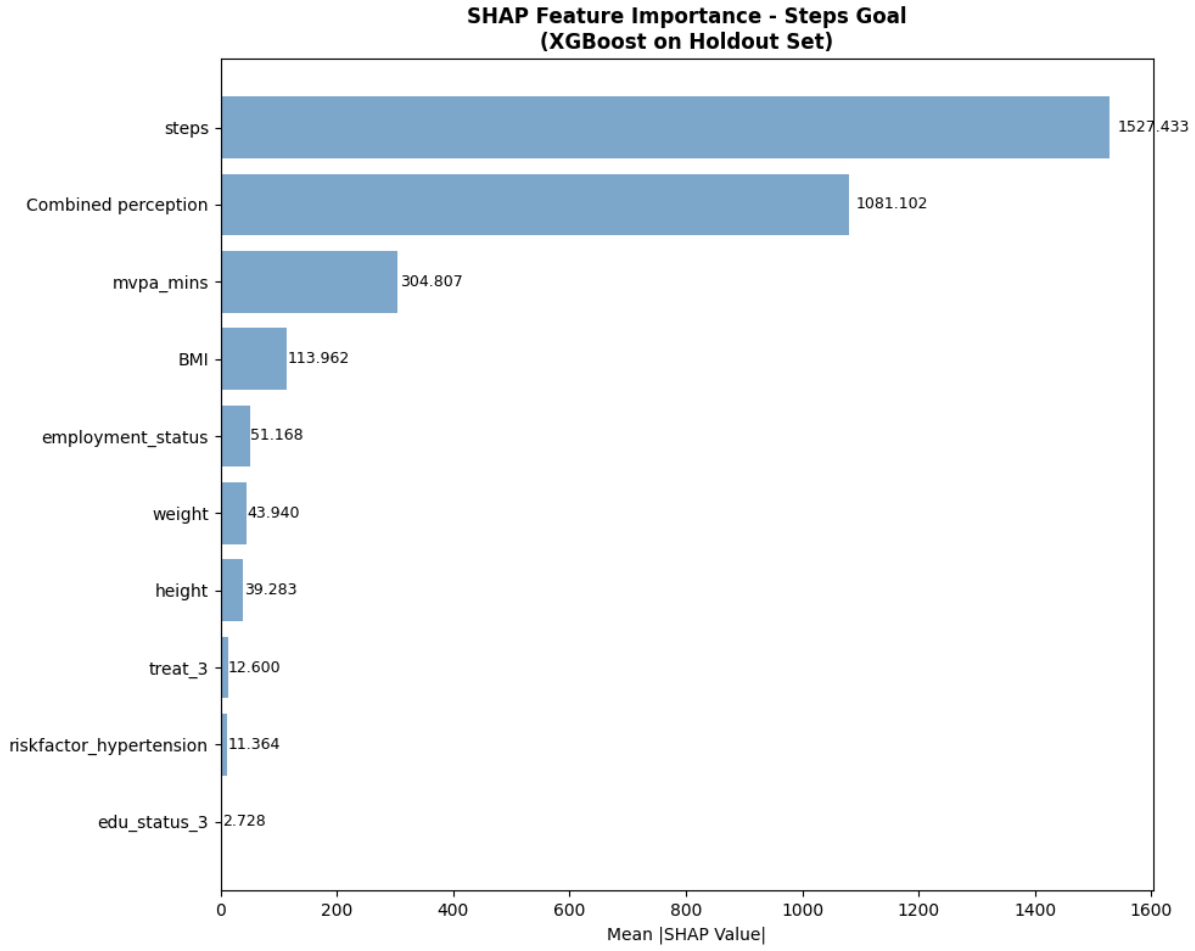



*Figure 3.6 Feature importance XG Boost*

Extra Trees and XGBoost had the best performance out of all the models, as measured by the $R^2$ score (0.8959 and 0.8880 respectively). XGBoost was selected as the final model, due to the following reasons:

i) XGBoost could perform well with both linear and nonlinear data. If new patterns were to emerge within the dataset in the future, XGBoost will be better able to handle them.

ii) A wide range of hyperparameters were available for XGBoost to allow for finer refinement of the model.

iii) The XGBoost model will deal with any missing values in the dataset if missing values are present within the data collected in the future.

iv) The execution speed and model performance of XG Boost are better

v) XGBoost may also help with feature selection

Figure 3.7 illustrates the relationship between the actual PA counts and the predicted PA goals. There is a strong linear relationship between the actual and predicted PA goals. This is reflected by the high $R^2$ values.

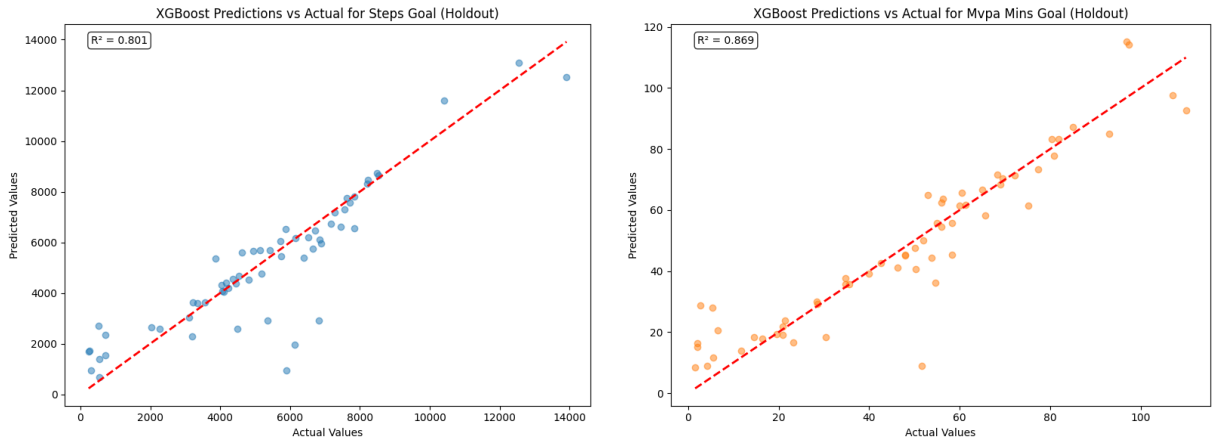



*Figure 3.7 Comparison of actual PA goals and predicted PA goals using XGBoost*

Figure 3.8 demonstrates the residual analysis for PA goal prediction. There is a greater variance at lower predicted values compared to higher values for both step count and MVPA minutes.

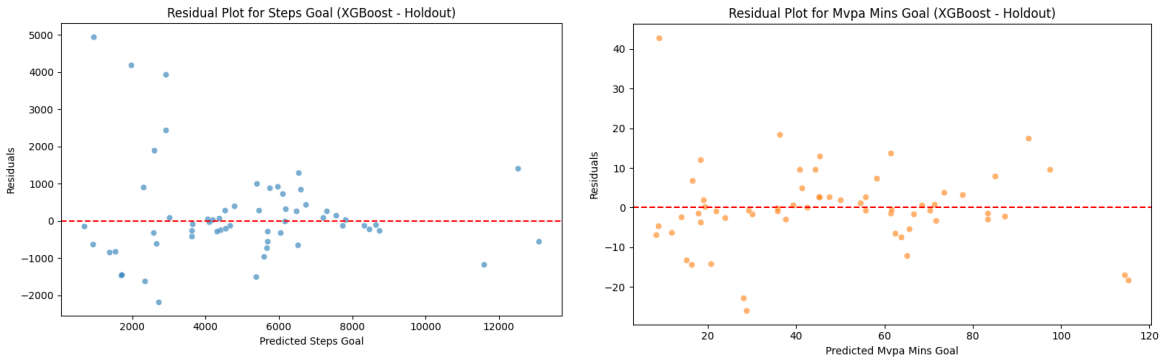



*Figure 3.8 XGBoost residual analysis for PA goal prediction*

Based on the XGBoost model, several features were identified as important in their contributions towards the predictions. The initial step count was the most important, with a relative importance of 47.9% (Table 3.5). Other features included participants' weight and perception. Hypertension as a risk factor was given a lower ranking in terms of feature importance.

*Table 3.5 Top features contributing towards the predictions and their relative importance*

| Feature | Mean Absolute SHAP | Relative Importance |
|---|---|---|
| **steps** | 1527.4331 | 47.90612 |
| **Combined perception** | 1081.1017 | 33.907467 |
| **mvpa_mins** | 304.80695 | 9.559907 |
| **BMI** | 113.96223 | 3.5742898 |
| **employment_status** | 51.167923 | 1.604821 |
| **weight** | 43.940205 | 1.3781322 |
| **height** | 39.28306 | 1.2320664 |
| **treat_3** | 12.600373 | 0.3951957 |
| **riskfactor_hypertension** | 11.364401 | 0.35643092 |
| **edu_status_3** | 2.7279541 | 0.08555903 |

## 3.4 Discussion

In our study, we developed an ML algorithm that was capable of successfully predicting PA goals for CR patients using their baseline characteristics and current PA levels. We trained and tested several ML models, including linear regression, ridge regression, XGBoost, K-nearest neighbour and random forest regressor. The prediction capabilities of these models were evaluated using $R^2$, MAE and RMSE. Based on the $R^2$ value, extra trees, random forest and XGBoost regressor performed the best with values over 0.80. On the other hand, linear, ridge and lasso regression have the lowest performance metrics with cross-validation $R^2$ values lower than 0.6.

Among the models that were evaluated, the XGBoost regressor performed well with a $R^2$ value of 0.88. XGBoost model has several advantages over other models, including its

scalability, ability to tune hyperparameters, efficiency in performance and speed and ability to handle missing values automatically without the need for other interventions. It has also been widely used in healthcare for tasks including predicting postoperative adverse outcomes after emergency surgery for acute type A aortic dissection and predicting in-hospital/30-day mortality after adult cardiac surgery (162, 163).

It is also important to note that the original OPTICARE dataset had several features or data fields that were not relevant to this study. For example, it captured physical activity levels at 3 months, 12 months and 18 months. As the RECAP trial is an 8-week programme, we omitted these data points from the training dataset.

One of the challenges with this dataset was the limited amount of data that was available. One option to overcome this problem would have been to create a synthetic dataset based on the original dataset using the Conditional Tabular Generative Adversarial Network (CTGAN). This approach has been previously used to generate synthetic data based on a smaller sample of real-life data (164, 165). Carefully training an algorithm is a crucial step to ensure the quality of the predictions made by an AI model. Synthetic data can be used to overcome the challenges associated with data confidentiality as well as data scarcity (166). A review of tools used to generate synthetic data in healthcare found that deep learning (DL) based synthetic data generators were commonly used in healthcare, with Python being the most commonly used platform for data generation (166). CTGAN is a DL-based data generator that is effective in generating tabular data which is capable of handling complex high-dimensional data. However, they require hyperparameter tuning to overcome issues, including mode collapse. Mode collapse occurs when the output produced is less diverse than the original dataset (166). A study which employed CTGAN to generate synthetic data and analyse survival outcomes found that CTGAN outperformed other models. The authors also demonstrated that the generated data closely resembled the real data that was used in the study (167). However, synthetic dataset generation may not be effective when used on a smaller dataset (168). Therefore, in our study, synthetic data generation wasn't employed to reduce the risk of introducing further bias. This could be an approach that could be explored further when more data has been collected.

The quality of predictions made by an AI algorithm is dependent upon several factors, including the quality of training data, features, model selection, and hyperparameter tuning. Among these, a fundamental predictor is the quality of the underlying data and the selection of features (169). Certain variables may have a higher predictive power, and various variables may also interact with each other, contributing to the predictions (170). Multicollinearity is a statistical concept where two or more independent variables are highly correlated and may mislead the model into treating some features as individually important, resulting in overfitting (171). In our study, for example, variables included step count and MVPA minutes, which may interact with each other to influence the predictions (172). This relationship must be studied further in larger studies.

In the development of this ML model for prescribing PA goals, a multidisciplinary team was involved, including a professor in cardiothoracic surgery, lecturer in machine learning, associate professor in statistics and ML, specialist CR physiotherapists, senior cardiac nurses and exercise specialists. The algorithm and intervention were developed by the lead author (PW).

Our approach for calculating the predicted or goal PA counts at week one had several limitations. As we did not have access to the weekly PA count as part of the dataset, we calculated an approximate figure for the PA count at week one. Our calculation, which involved subtracting the week 0 PA count from the PA count at three months and dividing the value by 13 to determine the weekly change in PA count, assumed a weekly linear increase in the PA counts. We then added this value to the week 0 PA count to derive the predicted goal PA count at week one. This calculation assumed the change happened uniformly across all 13 weeks. Furthermore, it did not capture the true pattern of change that happened weekly.

Another limitation of our study was the approach employed for calculating a perceived exertion rating using the data from the OPTICARE study. It assumed the percentage increase in PA correctly reflected patients' perceived exertion. However, it may not take into account all factors influencing their perception. It is also worth noting the PA data that was used to derive a figure for perceived exertion was collected at the three-month mark. This may not always be an accurate reflection of patients' actual perception of exertion during the early stages of CR, such as at week one.

Following the conclusion of Phase I of the RECAP trial, the ML model will be retrained. This will expose the model to real-life data without the need to use the feature-engineered variables for week 1 PA levels and perception.

In employing AI, particularly in healthcare, the perfect dataset may not always be available. This often leaves researchers with not many options but to employ approaches such as synthetic dataset generation and engineering features. This will allow clinicians and developers to move forward and develop novel interventions which can help advance healthcare. This process would also allow them to collect new, more specific data, which in turn may be used to validate and refine their algorithm.

Future work will employ this model in a home-based CR programme, the RECAP Trial (ISRCTN: 97352737). Even though the primary objective of the RECAP trial will be to determine the feasibility of conducting a larger RCT to evaluate the effectiveness of the home-based CR programme, it will also allow us to validate our ML model. We will collect weekly PA data and perception scores, as part of this study, which will also enable us to refine our model beyond the assumptions we have made in the training dataset when feature engineering was performed. Furthermore, we will compare the algorithm-generated PA goals with recommendations from healthcare professionals.

## 3.5 Conclusion

In this study, we tested several ML models to determine which is the most appropriate to accurately prescribe PA goals. We identified that several models performed well based on metrics including coefficient of determination ($R^2$), root mean squared error and mean absolute error. XGBoost was used as the model for the prescription of PA goals due to its built-in regularisation mechanisms to mitigate overfitting and its ability to capture potential complex non-linear relationships that may emerge in the future. It is also computationally efficient optimised for both memory usage and speed. This ML model will be used in future work as part of a home-based CR programme.

# CHAPTER 4

# 4. Development of the Mobile Application for Patients and Web Portal for Staff and Initial Evaluation

## Key Learning Points from this Chapter

- This chapter discusses developing and evaluating the RECAP mobile application and web portal.

Development of the Mobile Application for Patients and Web Portal for Staff and Initial Evaluation

- The Flutter framework was used to create a functioning mobile application to aid a home-based cardiac rehabilitation programme, and the Python programming language was used to create a web portal for staff to monitor participants. An evidence-based approach backed the software design and development process.

- Actigraph accelerometers facilitated the collection of participants' physical activity data. The devices were successfully linked to function with the RECAP mobile application.

- The mobile application and the web portal were evaluated in an alpha testing phase using automated test scripts, usability questionnaires, qualitative interviews and app analytics. This demonstrated that both software was usable but highlighted areas that need improvement. These areas were addressed in the following iteration of the software.

- The next stage of the software evaluation process (beta testing) will involve testing it on real cardiac patients who are post-acute coronary syndrome or cardiac surgery

# 4.1 Introduction

## 4.1.1 Mobile applications in healthcare

In our current world, the use of a mobile phone is inevitable. The use of computer automation is becoming more and more common and is a part of our everyday life. Examples include automatically filtering spam emails from our email accounts and using digital assistants like Siri and Alexa to answer phone calls. Mobile applications may be downloaded on a smartphone. The use of smartphones and mobile devices has increased significantly over the last few years, with 36% of the world's population having smartphones in 2018 compared to only 10% in 2011 (173).

Mobile applications have impacted several industries, including healthcare. Mobile phone applications (mHealth apps) can improve patient's access to healthcare and influence how patients engage with their healthcare providers in a positive manner (174). mHealth is defined as "medical and public health practice supported by mobile devices" (175). They may also give the patient more autonomy and control over their health, give patients a sense of regular contact with their clinicians and allow continuity of care, particularly when regular monitoring is involved (174). Mobile applications have a range of applications in healthcare, including their use in cardiac rehabilitation in cardiology and treating sleeping disturbances at a population level in psychiatry (176, 177).

Mobile applications may enhance the delivery of healthcare services and can be used to improve access to healthcare in several ways. Remote monitoring of patients, such as recording ECGs in real-time, may allow the diagnosis of abnormal heart rhythms (177). They may also help patients to be more compliant with their medications and promote healthy behaviours (177).

Despite the several benefits mobile apps may offer, they also come with their caveats. For example, improper mobile app usage and data handling by app developers may lead to privacy concerns (178). As healthcare apps become more mainstream, they may attract

threats from hackers (179). Some patients may also not trust a mobile app their healthcare provider provides. Therefore, it is important to validate and certify mobile apps before they are used in a clinical setting (180).

New studies evaluating mobile apps are constantly being conducted worldwide. An RCT concluded that a mobile app effectively improves mental health and promotes self-management of patients with hypertension (181).

Implementing a mobile app-based healthcare system in the NHS can be challenging as it needs to be backed by evidence and can require a lot of time and funding (182).

### 4.1.2 Behavioural change techniques (BCTs) in mobile applications

BCTs are "coordinated sets of activities designed to change specified behaviour patterns" (183). These techniques are very important in clinical medicine and public health.

Mobile health applications can help change a person's behaviour. Mobile apps may employ various behavioural change techniques, including goal setting, action planning, feedback on behaviour, self-reward and punishment (184). A systematic review of BCT used by mobile apps found that goal setting, self-monitoring of behaviour, feedback on behaviour, prompts/cues, rewards, and social support have the most potential association with engagement with mobile behavioural change interventions (184). The study highlighted the importance of using mixed methods when evaluating engagement with mobile apps, as engagement can be determined using data captured via qualitative research, self-reports, questionnaires and app tracking (184).

A content analysis of mobile apps that promoted medication adherence found that action planning and prompts/cues were the most common combination of BCT and were found in 91.4% of the apps analysed (185). The second most common combination was action planning, feedback on behaviour, self-monitoring of behaviour and prompts/cues, which was found in 33.9% of the apps (185). The authors concluded that there is a need for research linking behavioural change research and software development.

BCT has also been found to help with weight loss in people who were recently diagnosed with diabetes (186). This study found that goal setting, goal reviewing, and social support were particularly effective in promoting weight loss and increasing physical activity. Researchers in this study taught the participants BCTs to help maintain physical activity dietary intake, and promote medication adherence and smoking cessation.

However, a systematic review of the effectiveness of BCTs in improving older adults' physical activity levels found that commonly used BCTs that were successful in younger adults may not be effective for the older population (187). Findings from this study demonstrated that BCT, such as goal setting and providing feedback on performance, were linked to lower levels of physical activity (187). This study included adults with a mean age of 69 years who were community-dwelling and were not restricted to a certain clinical condition. However, barrier identification/problem-solving, rewarding successful behaviour and modelling/demonstrating the behaviour were associated with higher physical activity levels (187). Further research is needed to identify which BCTs may effectively improve the PA levels of older patients following heart disease.

A systematic review of the effectiveness of BCT in eHealth-based CR found that graded tasks consistently improved physical activity levels (188). These were tasks which increased in difficulty over time. The study also looked at medication adherence and found that problem-solving, action planning, feedback on behaviour and self-monitoring were associated with better medication adherence. The interventions in this review were most commonly facilitated via mobile text messages or an app (188). The study concluded that certain BCTs may be more effective at targeting specific health behaviours than others.

### 4.1.3 Self-monitoring and feedback: PAM devices

Monitoring one’s physical activity levels is important in identifying areas that could be improved. One way to monitor a participant’s PA levels is by using a physical activity monitoring (PAM) device. Pedometer-based PA activity promotion programmes have been

shown to increase the daily step count (189). A PAM device could be integrated into a mobile app to supplement a CR programme.

Physical activity monitoring (PAM) devices are widely used in CR programmes to record the PA levels of participants (190).

A systematic review of using pedometers to increase PA concluded that using a pedometer is linked to significant improvements in PA and a decrease in body mass index and blood pressure (190). The study had 2767 participants with a mean age of 49 years, including patients with coronary artery disease. In the RCTs that were included, participants who had access to a pedometer had a step count of 2491 more than the control arms (95% confidence interval [CI], 1098-3885 steps per day, $P < .001$) (190).

An RCT which examined the effectiveness of a PAM device-based intervention to increase PA employed goal setting, and participants were given a pedometer (Yamax Digiwalker 700B) at the initial visit. As part of the intervention, they received phone calls during which they were guided to set goals and received behavioural counselling (191). The authors concluded that the intervention increased the PA level of participants following a CR programme.

An RCT involving 215 patients referred to a CR programme but did not attend the programme offered its participants a pedometer (Yamax Digiwalker 700B) for self-monitoring and goal setting (192). Participants in the intervention arm received phone calls at set time points and were provided with behavioural counselling and goal-setting guidance. Participants in the control arm received no phone calls and were only provided with PA information brochures. The authors demonstrated that the intervention increased the PA levels of patients who previously did not attend a CR programme (192). The fact that the participants consented to participate in this home-based CR programme, having previously not been able to attend a formal CR programme, suggests that they were willing to try alternative approaches to CR.

A systematic review of adherence to PAM devices in adults with cardiovascular disease found that this area hasn't been well-researched (193). Among the studies included in the review, the mean adherence was 59.1% at the final follow-up. A randomised controlled trial in the study demonstrated that using a smartphone app as part of the intervention improved adherence to the CR programme (194).

The use of PAM devices may benefit some patients more than others. A systematic review and meta-analysis of the use of PAM devices as a tool to promote daily PA levels in patients with COPD found that patients who already have a daily step count of 4000 steps or more may benefit more from PA promotion programmes (189). Therefore, a patient's baseline fitness level may be important when determining if a PAM device-based programme may benefit them.

Mobile apps that automatically recorded participants' data and provided daily feedback about their progress were superior to those that simply offered education or encouragement (195). The authors of a systematic review of the use of mobile apps for improving physical function capacity in CR patients suggested this may be because of the difficulty in sustaining motivation when the participants had to manually record their data frequently (195).

### *Dashboards*

Mobile apps may allow patients to monitor their progress within a CR programme as it can display data captured via a PAM device. A dashboard, on the other hand, could enable staff members at a CR centre to monitor their patients' progress.

In a feasibility study of a smartphone-based CR programme in a population of veterans, a coach (a cardiology physician assistant) could remotely monitor the participants via an online dashboard (196). It also allowed the coach to develop personalised exercise plans for each participant with access to a mobile app. Participants could log their vital signs and review educational materials via the mobile app. It also sent them daily reminders to exercise (196). The authors concluded that the programme was feasible and acceptable for low to moderate-risk, middle-aged veterans with CHD.

Clinical trials should focus more on interventions that could automatically detect participant's vital signs and physical activity levels and send them to their healthcare provider (195).

### 4.1.4 Action planning

Action planning may involve a shared decision-making process in which goals are set, and a structured plan is developed to achieve those goals (197). Having a structured framework can give patients a realistic approach to reaching the targets they have set for themselves. Successfully achieving goals may increase self-efficacy, motivating them to reach increasingly difficult targets (197).

Weekly action planning with the input of specialist healthcare professionals could improve patient participation and increase adherence to and effect of rehabilitation programmes (198).

Action planning could help patients reach their goals faster. Furthermore, coping planning could help them to successfully deal with potential barriers (199). Considering patients' priorities and addressing any barriers to achieving physical activity targets could increase engagement with healthcare professionals, improve adherence and outcomes (200).

### 4.1.5 Goal setting

#### *Effectiveness of goal setting*

Personalised goal setting allows us to set custom goals for each patient based on their past behaviour. Their last week's step count may be used to set step count goals for the following week. Several studies have examined remote cardiac rehabilitation programmes using adaptive goal setting. This will ensure the goals are challenging but, simultaneously, suited for that individual.

Two studies which used a personalised approach to setting goals for the next day using the steps taken in the past 10 days found that it was superior to setting static goals (for example

10, 000 steps per day) (201, 202). In these two studies, the research team used the 60th percentile from the last 10 days' step count as the goal for the following day. For example, for one given participant, the daily step count over the previous 9 days (ranked from the lowest to the highest) was 1250, 1332, 3136, 5431, 5552, 5890, 6402, 7301 and 10,103. In this case, 5890 (60th percentile) was used, and this was rounded up to 5900. This was then prescribed as the following day's step count target. In both of these studies, the authors found that adaptive goals were superior to static goals.

A study investigating the effectiveness of an automated mobile app-based goal-setting programme found that personalised daily step goals set using machine learning are superior to static goals (10,000 steps per day). However, the study participants were staff members at the University of California, Berkley and weren't participants with a specific medical condition (203). The ML algorithm in this study used the participant's past step count and goals to prescribe daily step goals.

A study involving 45 participants found that a cardiac rehabilitation programme using personalised step-count goals may help increase physical activity levels. In this study, participants worked individually with a nurse or physiotherapist, setting daily step count goals. These goals were reviewed weekly and involved the input of an exercise specialist (204).

The Borg Rating of Perceived Exertion (RPE) scale, developed by Gunnar Borg (205), is a tool that is often used in rehabilitation to measure a participant's effort, exertion, fatigue, and shortness of breath during physical activity. A cardiac rehabilitation study (206) involving 78 patients who had a myocardial infarction or coronary artery bypass graft surgery used their heart rate, BORG scale rating or a combination of both to gauge participants' level of exertion. They found that patients could gauge their exercise intensity well when instructed to exercise at a perceived exertion of 13. Participant training response was not very different across the three groups.

In a home-based cardiac rehabilitation programme (207), a physiotherapist visited the participants' home twice in a 6-week interval. The participants followed a personalised

exercise programme while following the international recommendations of 30 minutes daily exercise, 6 days a week. They were instructed to exercise at an intensity of 11-13 on the Borg Scale.

A national survey (208) of 1470 cardiac rehabilitation programme directors registered with the American Association of Cardiovascular and Pulmonary Rehabilitation was conducted in 2022. The survey found that the perceived exertion scale was the most common method used to prescribe exercise intensity. This was followed by a resting heart rate of +20-30 bpm. However, 55 formulas for calculating a target heart rate or range were reported. Furthermore, the survey found variation in the exercise prescriptions among staff members in the same programme. This was the case in 40% of programmes. Therefore, it is evident that there is a lot of variation in the exercise prescriptions of different programmes.

### *Level of difficulty of goal setting*

In an RCT looking at the effectiveness of a home-based CR programme using a mobile app, patients were given exercise goals and encouragement every two weeks. In the intervention arm, goals were adjusted based on the Borg scale using the data the participants recorded in the mobile app. If the Borg scale rating was not between 11 and 13, a healthcare professional adjusted the exercise targets set for the participants (209). Participants in the control arm received exercise targets based on questionnaires. In this study, the primary outcome measure was maximal oxygen consumption. The authors found that the mobile app-based intervention improved exercise capacity. However, no significant differences were observed between the groups.

### *Goal setting in cardiac rehabilitation*

An RCT that looked at the effects of a nurse-led eHealth CR programme for patients with CAD allowed patients to set goals with the help of a nurse with a specialism in CR (210). As part of the intervention, the nurse first assessed the patients' fitness level, and once goals had been agreed upon, they were uploaded to an online portal. They could upload their goal attainment data daily or weekly, after which they received automated motivational messages.

The patients were then added to a common group chat using the WeChat platform and encouraged to share experiences related to their progress in achieving their goals. The authors found that participants in the intervention group demonstrated significant improvements in their step count compared to the control group, who did not have access to the eHealth platform (210).

A systematic review and meta-analysis of eHealth for maintenance CR demonstrated that eHealth may improve physical activity levels, exercise capacity and quality of life and decrease systolic blood pressure in patients with coronary artery disease(211). Digital health interventions aimed at CR frequently use self-monitoring to achieve behavioural change (211). Novel PAM devices may also be supplied with mobile apps that display data allowing participants to monitor their PA levels. Therefore, it may be difficult to assess the effectiveness of an isolated BCT (211).

A retrospective cohort study of 629 patients investigated the effects of goal setting on diet scores and weight loss and concluded that goal setting was linked to better diet quality and weight loss during CR (212). As part of this programme, patients received exercise prescriptions informed by their target heart rate, functional capacity, or perceived exertion rating based on the Borg scale. 27.9% of the participants in this study were female, with a mean age of 63.4. Participants who set a dietary goal achieved significantly greater weight loss ($-2.17 \pm 3.08$ kg vs $-0.84 \pm 2.60$ kg, $P < .001$).

Social Cognitive Theory (SCT) is a behavioural theory that can be used to improve the self-management behaviours of patients (213, 214). It is frequently integrated into developing self-management and rehabilitation programmes (215).

In the development of rehabilitation interventions, previous research has identified three theories of behavioural change with evidence to support their effectiveness (216):

- Social Cognitive Theory (217)
- Goal Setting Theory (218)
- Health Action Process Approach (219)

Scobbie et al. proposed seven theoretical constructs based on the above theories, which could be useful in the development of a rehabilitation practice (216, 220):

1. Self-efficacy (An individual's belief in their ability to perform a specific task or achieve a goal)

2. Outcome expectancies (Beliefs about the expected results of engaging in a particular behaviour. If an individual believes their actions will lead to a favourable outcome, they may be more likely to engage in that behaviour)

3. Goal attributes (Important characteristics of a goal, including how specific, measurable, achievable, relevant and time-bound they are)

4. Action planning (Creating a plan that outlines achieving a set goal, including the steps needed, resources required and a timeline for each action).

5. Coping planning (This includes strategies for overcoming potential barriers which may arise while pursuing a goal. Anticipating challenges and preparing for them may increase the likelihood of achieving that goal.)

6. Appraisal (Regular evaluation of one's progress towards a goal. This may allow the identification of areas for improvement)

7. Feedback (Feedback on performance in relation to achieving the goal)

## 4.2 Development of a mobile application

The development of a mobile application consists of several stages (221), which can be summarised as follows:

1. Planning and preparing the content: determining the requirements of the mobile app
2. Designing and development of the mobile app, including the front end and the back end
3. Testing the mobile app: consisting of alpha testing and beta testing
4. Reporting to the stakeholders
5. Regularly updating and improving the content and the software

### 4.2.1 Planning and Preparing the Content

The first phase in the app's development was identifying the key components that should be included within the software.

Firstly, we conducted a systematic review of the approaches used by mobile apps in CR and market research of the apps in app stores. The market research was conducted with the help of NHS Innovation Southeast. We evaluated the contents of existing home-based CR programmes, including their strengths and weaknesses.

For example, one of the most well-studied and widely used home-based CR programmes is the Heart Manual (222). It was developed by Lewin and the team in 1991 and launched in 1992 (223). A clinical study of the Heart Manual reported that it was effective in reducing levels of depression and anxiety, and patients reported a better quality of life and reduced admissions to the hospital and presentations to the GP (222, 223). The Heart Manual has been used to treat around 14,000 patients per year worldwide (223). A systematic review of the Heart manual concluded that it is as effective as hospital-based CR in several domains, including psychological, behavioural, service and cost outcomes (223). Following the success of the Heart Manual, a digital version of the resource was later developed (224). However, it couldn’t automatically personalise exercises or goals for the participants (224). Furthermore, it hasn’t been as well studied as the original version.

Finally, the initial content of the mobile app, the staff web portal and the machine learning algorithm was discussed with an expert panel which included specialists who were CR physiotherapists, nurses, research nurses, two professors in cardiothoracic surgery, an associate professor in mathematical science, an assistant professor in machine learning and the academic cardiovascular research team with expertise in trial design and delivery.

### 4.2.2 Designing and Development of the Mobile App

Mobile app development is a complex process which can take several months (225). Mobile apps may be developed on a single platform/operating system (OS) like Apple or Android (225). A native app is developed specifically for a single platform, taking maximum advantage of the features and capability of that OS. A hybrid app, on the other hand, can run on multiple platforms (226). However, it may not be able to access a particular OS's capabilities. Both native and hybrid app development have their advantages and disadvantages. A native app can provide a better user experience. On the other hand, a hybrid app can run on multiple platforms and generally takes less time and resources to develop (226).

Application development can broadly be divided into frontend and backend (227). It is via the front end the user interacts with the application or the programme. This includes application components such as the icons, buttons and text boxes. On the other hand, the backend is responsible for handling the internal workings of the business logic (227). The front end communicates with the back end to execute the application's functions.

One of the main components of the front-end is the User interface (UI). It helps bridge the gap between the software code and the end user. UI is the visual manifestation of the software and includes elements such as text, images, buttons, navigation systems and dropdown menus. A mobile app, including its text and media, can also be a very effective education tool (228).

Therefore, it is important to design and develop a UI that is accessible, usable and inclusive (229). Mobile app stores such as Apple and Google provide guidelines for UI development. However, creating a UI for older adults needs special attention. Simple components of the design, such as the size of the text, placement of buttons and spacing between words, may impact how easy it is to use a mobile application (229). The graphical UI must also adapt to different screen sizes (225). For example, a mobile phone screen's size will be different from that of a computer or a mobile tablet. UI is responsible for 50% of the code of a device, and issues in this area can significantly affect the user experience (230). To develop and improve the UI design of an application, a think-aloud approach may be employed (230). Furthermore, the system usability scale (SUS) can be used to evaluate a mobile application, including its UI (Figure 4.1) (228).

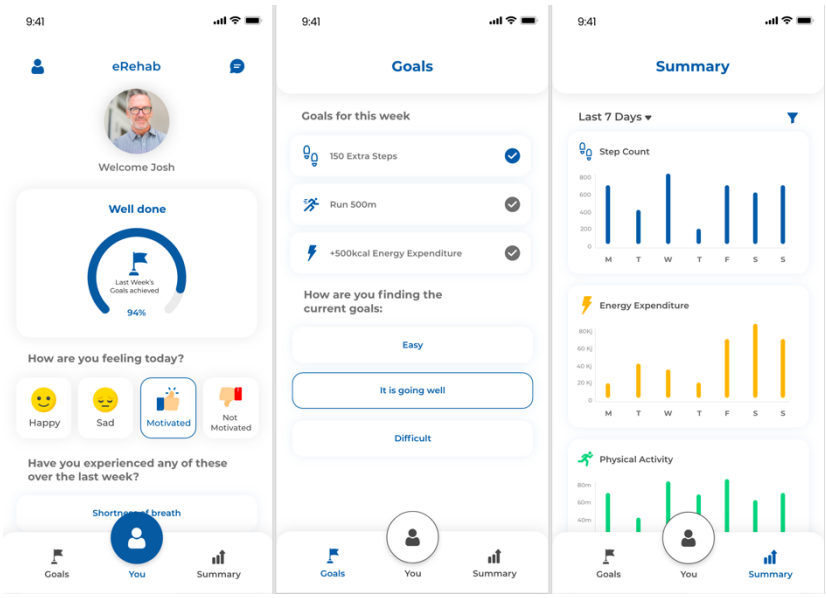



*Figure 4.1 An initial design of the UI of the mobile application showing three different screens*

Older adults may have difficulty using certain complex types of navigation control used by some mobile apps and struggle to use the keyboard within the app (229). A study which evaluated the UI of a mobile app for older adults made several suggestions, including the home screen menu should be utilised as a safe point of return; making the back button

available as it can allow users to return to where they were previously; provide ample spacing between items and use icons alongside text (229).

Most mobile applications will store users' data, including their names and email addresses. This data is stored in the application's backend and retrieved periodically when needed. Caching refers to storing frequently accessed data on a user's device, eliminating the need to constantly retrieve it online. This approach is particularly helpful in mobile apps where an internet connection may affect the app's performance, reducing the need to depend on the mobile internet network (231). Since the amount of storage on a mobile device and the caching storage is limited, it is important to cache only the frequently accessed data. However, one of the challenges is deciding which data to be cached (231). An efficient caching strategy can improve mobile app response speeds and user experience (232). Furthermore, it can also reduce energy consumption, preserving the mobile device's battery life (232). The caching approach can further be improved by analysing content popularity and determining which aspects of the data are most frequently accessed (233). However, to optimise the caching strategy, testing the mobile application on real users may be necessary.

Most mobile apps available today may allow users to create an online profile and sometimes store data such as their name, age, or even location. In most cases, these data are not stored on the user's device but in an external cloud-based service. Google Firestore is an online cloud-based database provided by Google (234). It allows the application to store and retrieve the user's data when needed. Firestore is a NoSQL, document-oriented database where the data is stored in a JavaScript Object Notation (JSON) format (234). Google databases have previously been used in health-related research to store data (235-237).

A programming language is an artificial language that can communicate instructions to a computer or a mobile application (238). They can be used to create programmes or mobile applications. Various programming languages are available to develop applications, including Java, Dart, Python, Swift, C/C++ and React native (239).

Google released Flutter in 2016, a cross-platform framework that can be used to develop mobile apps (240). It is written using the Dart programming language, which Google developed (240).

Python is a general-purpose, high-level programming language that is free and open-source (241). It was developed by Guido van Rossum and released in 1991 (241). It can be used to develop applications for both web and mobile. In addition, Python is also used to develop artificial intelligence and machine learning algorithms (241). We used Python to develop our web portal and the ML algorithm (discussed in the next chapter).

After establishing the app's contents, paper-based mock-ups were developed using Adobe XD (Adobe Inc.) to help visualise the user interface. These mock-ups were then shown to 5 staff members (physiotherapists, rehabilitation nurses and exercise specialists) of the cardiac rehabilitation team based at the James Cook University Hospital. Following their feedback, the user interface was further improved.

The app prototype was developed using the Flutter Framework for the iOS and Android operating systems. Google's Firestore Database is used to store user data. All participant data are anonymised before it is transferred to the Database. Images of the app screens are given in the appendix.

Actigraph accelerometers were used to record participants' PA data. This was then transmitted to the participant's phone via Bluetooth and then sent to Actigraph's database/cloud from the Actigraph's app on the participant's phone via the internet. The next crucial step was to retrieve the PA data from Actigraph's cloud and place it onto the RECAP mobile app. This would allow the data to be processed by the ML algorithm to generate the exercise goals. We used Actigraph's Application Programme Interface (API) to retrieve this data from Actigraph's cloud. An API is a set of rules or protocols that allows two or more different software to communicate with each other and share data (242). Once this data was retrieved, it was sent to a secure online server with the ML algorithm (Figure 4.2). We developed a custom API for this purpose using Python. In the development of the API, strict security measures were followed to ensure the data was transmitted safely. The data was also

encrypted to protect against possible breaches (243). This involved removing participant-identifiable information from the data. The ML algorithm processed this data on the server to generate the weekly PA goals. This was retrieved via the same API and sent to the participant's RECAP mobile app. This process was automated to run without human input. Automation in programming has several advantages, including increased efficiency, reduction in human errors, and consistency and reliability (244).




*Figure 4.2 Diagram showing steps involved in the generation of PA goals*

### 4.2.3 Testing the mobile app

Software testing is the process of executing a programme or system to find faults (245). This is an important part of the software development life cycle (SDLC) and may account for over 50% of the costs and labour associated with creating new software. The process aims to establish whether the software serves its purpose (245).

Software testing can be done in several ways, as outlined below (246):

#### *Unit testing*

A software developer performs unit testing and involves testing small units of code separately.

#### *Integration testing*

Checks whether two or more units of code or integrations are working together well.

#### *System testing*

Involves testing the whole software as a system to establish if the software serves its intended function

#### *Acceptance testing*

Usually performed by the business owners to determine if the software is acceptable to the end users

#### *Regression testing*

It is the testing of the software once new changes have been made. Regression testing ensures that new errors aren't introduced to the system following the software updates.

#### *Alpha testing*

Performed by the developer inhouse before the software reaches external users

### *Beta testing*

Performed by the end user in the absence of a developer

Software testing can further be divided into black-box and white-box testing (246). Black box testing involves testing software without knowing the internal code or logic. The tester will provide the necessary inputs to the software to establish if it produces the output as expected. Black box testing is used to validate the external workings of the software without paying attention to the internal logic (246).

On the other hand, in white box (or clear box) testing, the tester can see the internal code structure (247). White box testing is usually performed by the developer who understands the code. White box testing is conducted at various stages in the software development cycle. White box and black box testing complement each other (247).

Software testing should be conducted systematically. It is essential to identify which areas need to be tested, how they need to be tested, what inputs must be provided to the software, and identify the expected output (246). A commonly used approach to this involves writing test cases. A test case is a documented pathway in which a software tester establishes whether a software or system works as intended (246). Components of a test case typically include a test case ID, title/description, preconditions (conditions that need to be met before executing the test case, such as the user needs to be logged), test steps, expected results, actual results, status (pass or fail) and postconditions (the state the software should be in after the execution of the event) if applicable (246).

Maintaining a log of the test cases can be helpful for test management use. This may contain the date the test was run, the person who conducted it, the version of the software that was involved and the result (pass or fail) (246).

Following the initial testing performed by the software developers, beta testing starts in the last stages of the software development cycle (248). During this stage, a specific group of people is selected to test the software or system before it is released to its target audience. Beta testing is done using a black box technique, as the testers cannot access the software's

internal workings. It provides an opportunity to integrate feedback from real users before the software is made available to the public (248).

Engaging service users and healthcare providers in the development stage of a technological system is an important step in their implementation and future use (249). Therefore, in developing the RECAP CR programme, we used both quantitative and qualitative data from cardiac patients and service providers to ensure the final product was acceptable and usable.

### 4.2.4 Reporting to the Stakeholders

Regular involvement and reporting to the stakeholders, which includes healthcare professionals, is an important component of intervention development (250, 251). Taking the needs of both healthcare professionals or service providers and users can ensure that both parties' expectations are aligned (250).

In the case of a home-based CR intervention development, the stakeholders may include healthcare providers (doctors, cardiac nurses, physiotherapists, rehabilitation coordinators), technology developers, researchers and academics.

Involving professionals from a range of disciplines could help understand the problem and generate new ideas (251). It can also help make complex decisions, drawing from the knowledge and experience of the team (251).

### 4.2.5 Updating and reviewing the contents

Mobile applications are constantly updated with the addition of new content or due to changes in the operating system on which they are running. In developing complex interventions such as a home-based CR programme, regularly refining the content, format, and delivery is particularly imperative (251).

Furthermore, users may discover errors in the software with continued use. If these are not corrected in time, it may cause user dissatisfaction (252). These errors could potentially affect the app's functionality and usability and even result in users uninstalling the app from their device, leaving negative reviews in the app stores (252).

## 4.3 Testing on Healthy Volunteers

### 4.3.1 Introduction

Following the development of the mobile app and the web portal, they were tested by the software developers. RECAP Trial Phase I was a usability testing study of the mobile app and the web portal. We aimed to recruit 15 patients to test the intervention before it was used in a feasibility randomised controlled study in phase II.

Before an intervention is used in real-life patients, it was very important to ensure it was tested on adults who weren't directly involved in development. Beta testing is conducted to test a product in different environments before its final release to the target audience (253). This phase is used to find any faults in the software that weren't flagged up previously and to reduce the chances of the technology failing (253). Beta testing is often uncontrolled (i.e. testing does not follow a set plan) as we may not always be able to predict what faults may be discovered during this testing phase (254).

Acceptance/qualification testing is another unique type of testing in which the technology is checked to see if it conforms to the users' requirements (254). This testing phase may or may not involve the technology developers.

In programming, a "bug" refers to a fault or a defect. This may include an incorrect programme code, state or execution (255). Therefore, "debugging" refers to the process in which we find and correct any faults (255). When a bug is identified (for example, a mobile app shutting down unexpectedly), it is vital to be able to reproduce that problem (255). This will allow a software developer to identify the cause of the fault and fix it (255).

In this study, we aimed to test the mobile app, accelerometers and web portal on healthy volunteers (staff members at the James Cook University Hospital).

**Aims**

The primary aim of this alpha testing phase was to identify any faults with the technology (including the mobile app and web portal) and rectify them before using the intervention on patients. We aimed to answer the following questions:

1. Does the accelerometer communicate with the mobile app: can it successfully transmit the PA data captured by the accelerometer?
2. Is the mobile app usable?
3. Analyse app analytics and answer the questions:

- How often do users open the app?
- What are the most used features of the app?
- How long does each user spend on the app per session?
- What percentage of users return to the app after the first use?
- What path do users take within the app?
- Where do users exit the app?
- Are there any app crashes, and how often do they occur?
- What is the average loading time for each screen of the app?

### 4.3.2 Methods

**Study design**

This study employed a mixed methods research design, including an initial quantitative assessment based on questionnaires and embedded qualitative interviews.

**Participants and recruitment**

We approached staff members based in the cardiac rehabilitation and research department at the James Cook University Hospital between the 20th of May 2022 and the 6th of July 2022.

We aimed to recruit a sample of 10 participants. Previous research has demonstrated that a small sample size may be sufficient to evaluate a new user interface design and discover any system errors (256, 257). The system usability scale has been shown to give reliable results even with a small sample size of 10-12 participants (258, 259).

Participants were eligible if they were employed in the cardiac rehabilitation or research department, had direct patient care responsibilities, either currently or previously and had an understanding of cardiac rehabilitation. They were also required to have access to a smartphone with an internet connection.

**Intervention**

Each participant was given an accelerometer and asked to wear it throughout the day, including sleeping. They were also shown how to download the mobile app on their smartphone (Apple and Android). They were given an information booklet to accompany the app. This booklet described each app screen in detail so the participants could refer to them if they had difficulty using them.

Participants were given goals in step count, calorie expenditure and moderate to vigorous physical activity minutes. For the first week, all participants were given a standard set of goals and encouraged to exercise at home.

Each participant was on the programme for 2 weeks and was encouraged to achieve the exercise goals set by the algorithm while following the exercise videos available within the app.

Development of the Mobile Application for Patients and Web Portal for Staff and Initial Evaluation

As part of the intervention, a web portal was developed to allow clinical staff based at the hospital to monitor patients and alter the exercise programme as necessary.

**Outcome measures**

We conducted qualitative interviews, asking the staff members about their experience with the app. The interviews were recorded, transcribed verbatim and analysed using thematic analysis. At the initial meeting, the participants were shown how to download the app from the app store, and they were given a set of tasks to perform during the interviews. These tasks included:

1. Signing into the app using their email address and password
2. Viewing the physical activity data (they were asked to presume the app had recorded their past physical activity)
3. View the physical activity targets that were set for them both in the form of a table and a graph
4. View exercise videos that were recommended for them
5. Enter text into the diary and save it
6. Record information about their mood and any symptoms, and rate their perceived exertion (based on the Borg scale)
7. View the motivational quotes displayed by the app
8. View their profile information, including their programme start date, week start date, participant ID
9. Sign out of the app

While performing these tasks, they were asked to talk aloud about their thoughts. Following the initial interview, the staff members were given an accelerometer and asked to use the programme for two weeks. Following this period, they were shown the staff web portal and think-out-loud interviews were conducted. Think-out-loud interviews have been previously employed to evaluate eHealth mobile apps (260). Participants were asked to perform a set of tasks, including:

1. Sign in to the web portal
2. View a list of the participants enrolled on the study
3. View a given participant's physical activity data using their participant ID
4. View the PA goals that have been prescribed for a given participant
5. Manually override and amend the PA goals that the ML algorithm has prescribed
6. Send a custom notification to a participant
7. Sign out of the web portal

Similarly, in the previous interview, they were asked to talk out loud about their thought process while performing these tasks.

Participants (healthy staff members) who took part in the app testing stage were allowed to use the web portal, and usability testing was conducted using a "Thinking-aloud" interview approach. This method has been previously used to evaluate clinical systems (261). It has been shown that with only five participants, 77-85% of the problems of a system could be found with the "Thinking-aloud" approach. (262) participants were asked to navigate the website during the interviews. They were asked to speak out loud what they were thinking as they performed a set of given tasks (including login to the web portal, viewing a list of patients enrolled on the rehabilitation programme, searching for patients using the patient ID, viewing patient-specific physical activity level data, amending exercise goals set by the AI algorithm and sending custom notifications to patients).

When they used the app for the two weeks in the beta testing phase, the app automatically logged any recorded errors. Firebase app analytics is a service provided by Google Firebase which provides mobile app developers with a comprehensive set of tools to track and analyse user behaviour (263). It can provide insight into a user's behaviour, including the number of times an app was opened, the amount of time a user spent on an app per session, and the number of times an app shut down unexpectedly (264). This data can be used to assess participants' engagement with the intervention. Previous studies have recommended certain metrics, including the number of total logins and total time spent on a programme, as variables which could be used to assess engagement with a mHealth intervention (264, 265). Firebase Crashlytics is another service Google Firebase provides that allows mobile app

developers to track when an app shuts down unexpectedly (crashes). An app crash can be a negative experience for the user, so a developer needs to identify and address the issues causing it.

### 4.3.3 Results

The demographics of the participants are shown in Table 4.1.

*Table 4.1 Demographic profile of participants*

| Variable | Values |
|---|---|
| **Age range** | 41 - 58 |
| **Gender** | |
| **Male** | 2 |
| **Female** | 12 |
| **Height range in cm** | 156 - 172 |
| **Weight range in Kg** | 50 - 89 |

13 staff members (Research nurses, rehabilitation nurses and rehabilitation physiotherapists) were recruited. All participants provided written informed consent.

Following the testing phase, participants completed the MAUQ and SUS questionnaires. The Curved Grading Scale (CGS) was used to interpret the SUS scores. This approach has been extensively used with SUS grading. (266) The average SUS score was 78.6, corresponding to a grade of B+ (Table 4.2). The MAUQ score was 5.4 out of 7.

*Table 4.2 Curved Grading Scale (CGS)*

| SUS Score Range | Grading | Percentile range |
|---|---|---|
| **84.1-100** | A+ | 96-100 |
| **80.8-84.0** | A | 90-95 |
| **78.9-80.7** | A- | 85-89 |
| **77.2-78.8** | B+ | 80-84 |
| **74.1-77.1** | B | 70-79 |

| | | |
|---|---|---|
| **72.6-74.0** | B- | 65-69 |
| **71.1-72.5** | C+ | 60-64 |
| **65.0-71.0** | C | 41-59 |
| **62.7-64.9** | C- | 35-40 |
| **51.7-62.6** | D | 15-34 |
| **0.0-51.6** | F | 0-14 |

Table 4.3 demonstrates participants' average physical activity counts across the two weeks.

*Table 4.3 Average Physical Activity Data of Participants*

| | **Average Daily Step Count** | **Average Daily MVPA Minutes** |
|---|---|---|
| *Week 1* | 6295 | 176 |
| *Week 2* | 6571 | 179 |
| *Percentage Increase* | 4.38% | 1.70% |

As part of this stage, we also assessed the goals/exercise prescriptions generated by the machine learning algorithm.

Participants were also asked to complete a set of given tasks on the mobile app and timed how long it took them to perform them (Table 4.4).

*Table 4.4 Completion rates and time taken per task by participants (N=13)*

| Task | Completion rate | Time taken for completion (seconds), mean (SD) |
|---|---|---|
| Signing into the app using their email address and password | 13/13 | 50 (15) |
| Viewing the physical activity data (they were asked to presume the app had recorded their past physical activity) both in the form of a table and a graph | 12/13 | 15 (5) |
| View the physical activity targets that were set for them | 11/13 | 10 (4) |
| Open exercise videos that were recommended for them | 11/13 | 7 (3) |
| Enter text into the diary and save it | 12/13 | 124 (30) |
| Record information about their mood and any symptoms, and rate their perceived exertion (based on the Borg scale) | 11/13 | 35 (16) |
| View the motivational quotes displayed by the app | 13/13 | 6 (4) |
| View their profile information, including their programme start date, week start date, participant ID | 12/13 | 9 (4) |
| Sign out of the app | 13/13 | 3 (3) |

## *Analysis of app analytics*

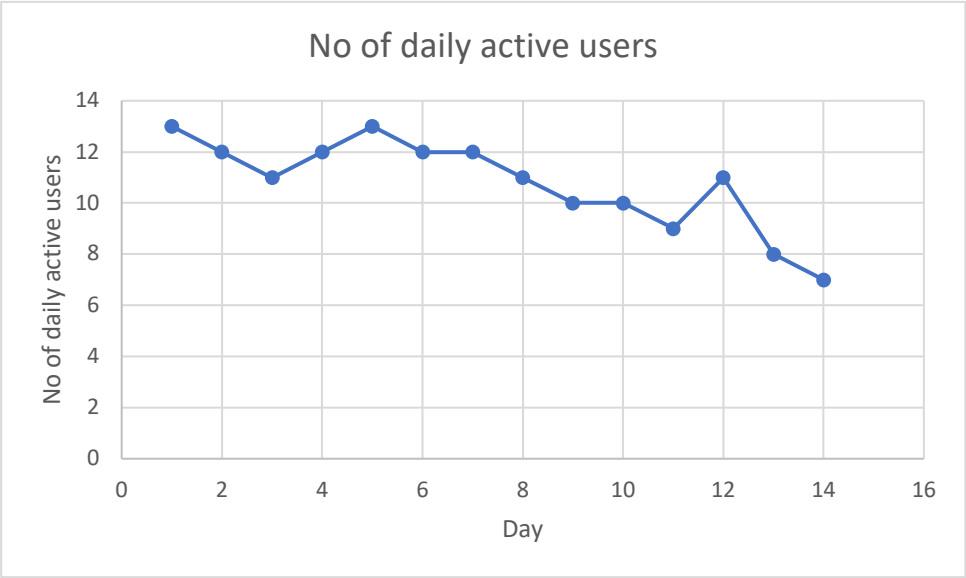



*Figure 4.3Number of daily active users*

Figure 4.3 shows the variation in number of daily active users. At the start of the study, 13 staff members downloaded the application. On the first day, all 13 participants actively used the app. On the second day, this dropped to 12, and there was a gradual drop in the number of active users over the two weeks. During the last day of the study, only 7 participants were active.

| Screen Name | Total time spent (%) | Mean time spent (s) |
|---|---|---|
| **Goals screen** | 54.1% | 45 |
| **Summary screen** | 15.2% | 15 |
| **Check-in screen** | 25.1% | 23 |
| **Home Screen** | 1.0% | 1 |

*Figure 4.4 Mean time spent on each screen*

Figure 4.4 demonstrates the mean time each participant spends on each screen. The highest percentage of time was spent on the "Goals" screen, while the lowest amount was spent on the "Home" screen.

Firebase Crashlytics revealed that the app crashed on 30% of the occasions when the screen containing the exercise videos was opened. The app terminated automatically, resulting in users having to reopen it. No crashes were reported in other areas of the app.

The screen containing the exercise videos also had a higher load time of 3200 milliseconds compared to the mean load time of 2300 for other screens.

### Web Portal Testing

The duration of each interview was between 15-30 minutes. The interviews were recorded and transcribed.

Following transcription, NVivo software was used to code the content of the interviews. The themes of the interviews are given in Table 4.5.

*Table 4.5 "Think Aloud" Usability Testing Results*

| Coding Category | Example quotes | Theme |
|---|---|---|
| **Navigation** | "It is obvious where everything is. I could easily find my way around the website."<br><br>"I would like to see the logout button on the top right corner." | The logout button was best placed in the top right corner.<br><br>The navigation was otherwise straightforward. |
| **Learnability** | "Straightaway knew what each button does."<br><br>"Oh, I didn't know that you could click on a patient's row to open up their page." | Users were easily able to learn the functionality of the web portal.<br><br>It wasn't obvious that they could click on each row corresponding to a patient to view more information about that patient. |
| **Errors** | "If I made any errors on the login form, it would warn me." | The web portal warned users if they made any mistakes on the login form or when searching for patients by their ID. |
| **Content** | "The page isn't overloaded with information. It shows just what I need to know."<br><br>"I don't know what s c and m stand for." | The web portal only contained the relevant information.<br><br>It wasn't very obvious that step count was abbreviated as 's', calorie count as 'c' and moderate to vigorous physical activity minutes as 'm'. |
| **Memorability** | "Once I've done something, I can easily remember how to do it again."<br><br>"An about page may help to act as a user guide if necessary." | Users were able to remember how to perform certain tasks easily.<br><br>An "About" page could provide user instructions as a reminder on how to perform certain tasks. |
| **Effectiveness and satisfaction** | "Overall, the site is easy to use, and I will have no problems using it myself." | Users were successfully able to perform the tasks given to them |

| | | |
|---|---|---|
| | | without much input from the interviewer. |

Following feedback from the participants, the web portal was further improved.

### 4.3.4 Discussion

In the development of software, testing plays a crucial part before it is deployed for its intended purpose. This is particularly important in mobile apps used in healthcare. Alpha testing enables developers and stakeholders to identify any issues with user experience design and development, while beta testing could highlight problems with usability, acceptability and safety (267).

It is important to identify any aspects of the design, performance, and functionality before using software on real patients. This alpha testing stage aimed to evaluate if the mobile app and the web portal performed as intended. The study demonstrated that both of these software were usable. This phase helped us to identify any errors in both the frontend and backend and to correct them (268).

Following the testing phase of the mobile app and the web portal, we identified several areas that could be improved to make the user experience better. A new version of the mobile app and the web portal was developed following our findings from this study. The main updates to the intervention are outlined below.

**Web portal**

*Design and Visual*

1. The area of the graph, which displayed the step count, calorie count and MPVA data, used the abbreviations s, c and m to represent each of the domains, which most participants (10/13) found confusing. We have written this in full form in the following iteration of the web portal.

2. Participants (7/13) expected the “log out” button to be at the top right of the screen. In the original version of the web portal, this was placed at the bottom left. We have moved the log-out button to the top right in the new version.

### *Functionality*

1. Participants (4/13) suggested that an “about” page which explained the features of the web portal might be helpful if users wanted to refer back to it. We created an “About” page, which outlined the various functionalities of the web portal.

2. In the current version, when the “log out” button was clicked, it would log the user out of the web portal immediately. However, participants felt it would be better if the system warned the user with a message such as “Are you sure you want to log out?”. This would prevent the user from being logged out if they accidentally clicked the button. In the next version of the web portal, a warning message was added to appear when the log-out button was clicked.

### *Performance*

1. Due to restrictions in the IT systems at the James Cook University Hospital, certain computers in the CR department prevented staff members at the hospital from accessing the web portal from the Windows “Internet Explorer” web browser. This was likely because the web portal's security status was deemed high risk due to a malfunctioning security certificate. A Secure Sockets Layer (SSL) certificate is a digital certificate that allows data to be transferred securely between a website and a web browser. It allows sensitive user data to be handled securely. However, some web browsers may warn the user of an SSL certificate issue (269). We have reinstalled the SSL certificate of the web portal, and the issue has been resolved. However, the web portal load times were much slower, up to 9 seconds, in the Internet Explorer web

browser compared to Google Chrome. Google Chrome performs better with certain web applications than other web browsers (270).

## Mobile app

### *Functionality*

1. 5/13 users stated that the app's bottom navigation bar didn't function as expected at times. Sometimes, when an icon was touched, it would not open the relevant page. On further investigation, this was found to be an error with the clickable area of the icon. This area was expanded further so it would be activated when a user touched this button.

2. The app was developed so that the "check-in" screen would automatically appear when opened on the sixth day of each week. The check-in screen prompted the user to enter a Borg rating for their exercises for that particular week. This rating was used to guide the following week's exercise prescriptions. However, in some instances, 3 out of the 13 users reported that this screen did not automatically appear on the sixth day of the week. This was due to an issue with the code that registered each user's programme start date. It incorrectly registered the start date as Monday even if a user didn't start the programme on a Monday. The code was amended to correct this.

As part of functionality testing, we also asked participants to complete a given set of tasks (Table 4.4) and recorded the completion rates and how long it took to perform these tasks. The majority of the participants were able to navigate the app's core functions. However, some users were unable to perform certain tasks such as view physical activity data (92% completion), activity goals (85% completion) or access exercise videos (85% completion). The considerable variation in the standard deviation for the time taken to complete these tasks may be a reflection of each user's technical skills, or it could be an indication of the need to improve the app's workflows. This area will be explored further in future studies.

### *Performance*

1. The mobile app crashed on 30% of the occasions when the screen containing exercise videos was opened. This screen also had a higher mean load time of 3200 ms than the mean load time of 2300 ms for other screens. This was a result of the exercise videos being stored on the mobile app itself. One way to address this was to not store the videos on the app and to load them from an external source. This meant there was less of a burden on mobile app storage. Following what we learned from this study, we implemented this change, and on subsequent testing, the load time for this screen was reduced to 2420 ms.

2. Some users (4/13) noted that the app visuals didn't always adjust depending on the mobile's screen size. As a result, some components of the UI, including text boxes and graphics, would be displayed outside of the screen, which meant they weren't visible. Upon investigation, it was found that there were issues surrounding the adaptability of the app to smaller screen sizes, such as iPhone 7. This was addressed in the newer version of the app.

3. Analysis of overall app analytics data revealed the app had a generally slow load time, which had a negative impact on user experience. On further investigation of the issue, it was found that some components of the app consumed a substantial amount of the phone's memory space, resulting in slow load speeds. This also meant there was a slight delay in the pages being rendered when a user switched from one screen to the next. This aspect of the performance was further improved by locally caching data directly on the user's mobile device, which significantly improved load times.

4. 8 out of 13 participants reported that there was a delay in the PA data being transmitted from the accelerometer to the mobile app. Internal testing of the code

was conducted to ensure there were no errors in the connection between the RECAP app and the accelerometers; no faults were found. The company (Actigraph), which supplies the devices was contacted about this problem. We were advised that the automatic "sync" function of the Actigraph technology wasn't always functioning as expected. Consequently, the app user handbook was updated, advising users to manually sync their accelerometers.

### *Strengths*

This study had several strengths. Most mobile apps are developed by external companies with commercial interests (271). The development process may not take into account best practice guidelines (272). In creating the RECAP mobile app and web portal, we followed an evidence-based approach to design the content and evaluate its performance. To the best of our knowledge, the RECAP software was the first to be developed (designed and coded) by a medical doctor (PW). Following the development process, the software was evaluated by a senior software engineer for quality assurance purposes.

During the testing phase of the mobile app and the web portal, we used several strategies to evaluate various aspects of the technology, including automated test scripts, think-out-loud testing, questionnaires, and app analytics.

### *Limitations*

One of the limitations of the alpha testing phase was the small sample size, as it was tested only on a sample of 14 users. Out of the 14 users, only two were male, and the rest were female. This is in contrast to the average CR population, in which a higher proportion of patients tend to be male. However, it is also important to note that in the alpha testing stage, the demographics of users don’t necessarily need to match the target audience. Furthermore, each participant only used the programme for two weeks. A longer use period may have allowed us to conduct a more thorough evaluation of the software.

In the beta testing stage of software, it is important to test it on users who match the demographics of the final end users to identify any specific issues that may arise for them (268). Following this alpha testing phase, we aim to test the software on real patients who care for post-acute coronary syndrome or cardiac surgery.

### 4.3.5 Conclusion

This chapter describes the development and initial testing of a mobile application and web portal for a home-based CR programme. Following testing on healthy volunteers, usability testing of the mobile app revealed the app was generally usable. However,
we were able to identify several key areas relating to aspects of the design, functionality and performance of the software, which were subsequently addressed.

As the next stage, we will test the software in real patients in phase I of the RECAP trial prior to using the mobile app and the web portal in a feasibility RCT.

# CHAPTER 5

# 5. Evaluation of the Mobile Application and Web-portal on patients referred for Cardiac Rehabilitation

## Key Learning Points from this Chapter

- This chapter discusses the evaluation of the RECAP Trial mobile application and the machine learning (ML) algorithm on real-life cardiac rehabilitation patients for the first time.

Evaluation of the Mobile Application and Web-portal on patients referred for Cardiac Rehabilitation

- The mixed-methods study found the mobile application to be highly usable, with participants, even those with limited technological skills, being able to use it without intensive prior training.

- The ML algorithm successfully prescribed participants physical activity (PA) goals, which did not require manual adjustment, while motivating them to increase their PA levels.

- Qualitative analysis revealed five key themes: the remote monitoring aspect of the intervention gave participants a sense of feeling safe, having goals motivated them, they valued the human touch provided by the routine phone calls, the technology was easy to use, and they appreciated the convenience the home-based programme offered.

## 5.1 Introduction

Cardiovascular disease (CVD) continues to be the leading cause of death worldwide, causing 6.2 million deaths between the ages of 30 and 70 years in 2019 (273). Morbidity and mortality associated with CVD may be addressed by addressing modifiable risk factors such as physical activity. Exercise is an essential factor in the primary and secondary prevention of CVD (274).

Personalised medicine (PM) entails personalising medical decisions and treatments to the individual based on their distinctive characteristics, lifestyle, environment and other relevant factors (275, 276). PM aims to provide more effective and targeted treatment to an individual, reducing the likelihood of adverse events (277). Health monitoring devices such as accelerometers may be used for PM as they allow the collection of critical health data that could be used to create an individual profile for the patient. Mobile applications may also provide advice, feedback and coaching that could benefit a patient (278). It is important to evaluate new interventions prior to their adaptation into clinical practice.

Usability testing is an important component of intervention development, particularly as older adults may struggle with technology (279). Therefore, it is particularly important to test new interventions before they are used in an RCT. Usability testing may involve various assessments such as questionnaires, interviews and log analysis of technology (279). These allow researchers to build a clear picture of the intervention's usability.

AI algorithms have been used explicitly in cardiology and cardiothoracic surgery to diagnose heart murmurs and detect ventricular dysfunction from electrocardiograms (280) (281). It has also been used to prescribe antimicrobials (282). To our knowledge, ML hasn’t been used to prescribe exercises for cardiac patients as part of a remote CR programme in the NHS. The RECAP Trial mobile app was designed to automatically prescribe physical activity goals for patients. As this was the first time the ML model was used on patients, all goals were prescribed by a healthcare professional. This was a crucial step and a safety measure, as AI can often make mistakes, especially when a new model is tested for the first time (283).

A mixed-method approach allows clinicians to gain a more comprehensive understanding of complex interventions, particularly in implementational research (284). In this study, we employed a mixed-methods approach to better understand the experiences of both staff and the participants. In reporting this work, we followed the Mixed Methods Reporting in Rehabilitation & Health Sciences (MMR-RHS) guidelines (285).

Qualitative methods offer a useful approach in the assessment of novel digital health interventions as they allow researchers to capture information which may otherwise not be captured through quantitative data analysis. Qualitative data can offer insight into participants' subjective perception of the intervention, including enabling factors as well as barriers to participation (286). This is particularly important when a new intervention is first tested or introduced to clinical practice. A systematic review on barriers and facilitators of user engagement with digital health interventions found that technical issues were often reported as a barriers to engagement, and people were more likely to engage if they were trained on how to use the intervention (287).

Qualitative methods may enable researchers to identify features and functionalities that are preferred by participants. A systematic review on the effectiveness, acceptability and usefulness of mobile applications for cardiovascular disease self-management found that patients found features including physical activity goal setting, recognition of achievements and motivational messages enabling (288).

Qualitative methods are often used during the beta testing stage of a mobile application to identify areas with potential for improvement. Findings guide researchers and software developers to create user-centred designs which could improve engagement and satisfaction (289). Insights from service users can also be used to guide the design and development of a mobile application in the initial stages of the development process (290).

## Research Aims

This study aimed to explore the staff and participants' experience with the intervention, assess the usability of the mobile app and the web portal and identify areas for improvement.

## 5.2 Methods

### 5.2.1 Study Aims and Objectives

In this mixed methods study, we aimed to assess:

1. The usability and acceptability of the RECAP Trial mobile application among CR patients
2. The appropriateness of the PA goals prescribed by the ML algorithm
3. The patient and staff experiences with the home-based CR programme through qualitative assessment

### 5.2.2 Study design and setting

The RECAP trial Phase I was a single-centre mixed-methods study with a pre-test and post-test design. Participants were recruited using consecutive sampling to the home-based CR (intervention) programme. As part of the study, participants participated in an 8-week home-based CR programme delivered using a mobile app powered by ML.

Patients referred to cardiac rehabilitation at the James Cook University Hospital who met the eligibility criteria were recruited between the 24th of January 2023, and the 25th of April 2023.

### 5.2.3 Participants and trial assessments

Eligible participants were those who had postcardiac surgery or admission for acute coronary syndrome that, had been referred for CR, were over the age of 18, had access to an Android or iOS mobile device and were able to provide informed consent.

We excluded participants, including those who were awaiting urgent surgery, had unstable angina, were pregnant or were currently enrolled in another interventional clinical trial or experiment where the intervention is considered likely to impact the outcomes of the RECAP trial.

As part of standard care, patients are invited for a preassessment clinic appointment following their discharge from the hospital. The baseline visits for the trial coincided with this appointment to reduce travel for participants. The final visit for the trial took place eight weeks after the baseline visit, following the completion of the CR programme. Participants were given the option to choose a site and time, where possible, as per their convenience.

During these visits, trial assessments were conducted by members of the research team or the CR team.

We conducted the trial assessments before randomisation after obtaining consent. The baseline assessments consisted of the 6MWT (291), EuroQOL 5-Dimensions (EQ5D5L) (292) and 36-item Short Form survey (SF36)(V.1.0) (293), Hospital Anxiety and Depression Scale (HADS) (294), Barthel Index (295) and clinical frailty scale (CFS) (Rockwood scale)(296).

At the final visit, participants completed the system usability scale (SUS), the mobile application usability questionnaire (MAUQ), and the questionnaires they had completed at the baseline visit. We also repeated the 6MWT.

As part of the study, a member of the CR team contacted each participant every two weeks to check their progress with the programme. They also spoke to them about the goals set for them using the ML algorithm. This ensured the goals were appropriate for each participant. For each phone call, the staff member filled out a form that recorded the content of the phone call. This was an essential step in the study as it was the first time the ML algorithm was used to prescribe physical activity goals for patients. During this stage, if the CR team deemed any of the goals set by the algorithm to be unrealistic, they had the option to amend the goals.

Participants who consented to the qualitative component of the study also took part in a semi-structured interview conducted during the final visit or via a phone call. We also conducted staff focus groups. The interviews were recorded, transcribed verbatim and analysed using thematic analysis (297).

### 5.2.4 Outcome Measures

The primary outcome of this study was the usability and acceptability of the intervention to the participants. Usability was assessed using the SUS and the MAUQ scores. Acceptability was evaluated using data from the qualitative interviews.

App analytical data was analysed following the intervention, demonstrating the most visited screen and how long each participant spent using the app and on each screen. We also investigated the crash reports, which recorded every instance of the app stopping unexpectedly during usage.

### 5.2.5 Statistical analysis

A summary of the number of participants screened, eligible, consented and declined was given. When a participant declined participation, we also recorded the reasons if it was provided. We presented the participants' baseline characteristics and used descriptive statistics (mean and standard deviation or median and interquartile range) to calculate the continuous variables. Categorical variables are summarised as frequencies and percentages.

The uptake and adherence to the intervention rates were presented as percentages.

### 5.2.6 Trial Procedures

As part of the home-based CR programme, patients were given an accelerometer to wear for the rehabilitation programme, which lasted for eight weeks. The RECAP Trial mobile app was installed on their phone during the first study visit.

### 5.2.7 Qualitative Study Methods

The RECAP Trial protocol has been previously published (1). The qualitative study design and analysis were guided by the normalisation process theory (NPT), a theoretical framework that explains how complex interventions and processes become integrated into healthcare systems (298). NPT recognises four main mechanisms: coherence, cognitive participation, collective action, and reflex monitoring (299). Table 5.1 demonstrates how the NPT constructs were used to inform our study design, qualitative interview questions and framework for analysis.

All patients (n=15) were approached to participate in interviews to understand their experience and usability of the intervention. No sampling took place.

All staff (n=12) involved in the care delivery of cardiac patients at South Tees NHS Trust were invited via email to participate in focus groups aiming to understand their experience with the intervention delivery and the use of the web portal.

PW conducted all interviews and focus groups. An academic foundation year doctor (JT) facilitated one of the staff focus groups. PW was known to the staff, having previously worked with them on research on a professional basis. However, none of the researchers were known to the participants. Patients were offered the option to participate in interviews during the final visit or at home via phone. Staff focus groups took place in the CR department at the James Cook University Hospital and were led by the lead author. Informed consent was obtained from both patients and staff before participation.

Participant interview guides and staff topic guides were developed with input from a clinical research fellow and surgeon in training (lead author), professor of cardiothoracic surgery, academic cardiovascular unit team staff specialising in trial delivery, cardiac rehabilitation specialist physiotherapists and nurses.

The focus groups were recorded and transcribed verbatim. Qualitative data management and analysis were conducted using the QSR NVivo (Version 12; QSR International, Doncaster, Australia) software. Reflexive Thematic analysis was used (300). The analysis was guided by Braun and Clarke's six-phase framework (300). This included familiarisation with the data, generating initial codes, searching for themes, reviewing the themes, defining and naming themes and producing the report. A hybrid (deductive, inductive) approach to analysis was used - a pre-determined set of codes was developed based on NPT and the research team's clinical experience; however, new theses were also identified inductively.

*Table 5.1 NPT constructs mapped to questions from the topic guide*

| NPT construct | Question from Topic Guide | | | Themes |
|---|---|---|---|---|
| | Intervention | Control | Staff | |
| Coherence | How familiar were you with the concept of home rehabilitation? | | What did you think the delivery of the programme would be like? | Health & Safety Benefits |
| Cognitive participation | What motivated you to take part in the programme? | | What motivated you to help with the delivery of the sessions? | Motivation & Goal Achievement |
| Collective action | What motivated you to do well in the programme? | | Did you feel well supported in your role during the programme? | Healthcare Support & Communication |
| Reflexive monitoring | What did you think could be done differently or improved? | | | Technology Experience & Usability |

### Ethics

RECAP trial received NHS research ethics approval from the Berkshire research ethics committee in September 2022 (IRAS 315483)(Appendix C). The RCT was registered on the ISRCTN trial database: ISRCTN97352737.

## 5.3 Results

### 5.3.1 Quantitative Study Results

Figure 5.1 illustrates the flow of participants through the study. A total of 20 patients were assessed for eligibility, and five were excluded due to not meeting the inclusion criteria or having declined to participate. Reasons for not meeting inclusion criteria included not having a diagnosis of ACS or having had heart surgery, as some patients were referred for CR for heart failure and not having a compatible smartphone. The two patients who declined to participate in the study later refused to enrol in standard CR due to going on holiday and work commitments.

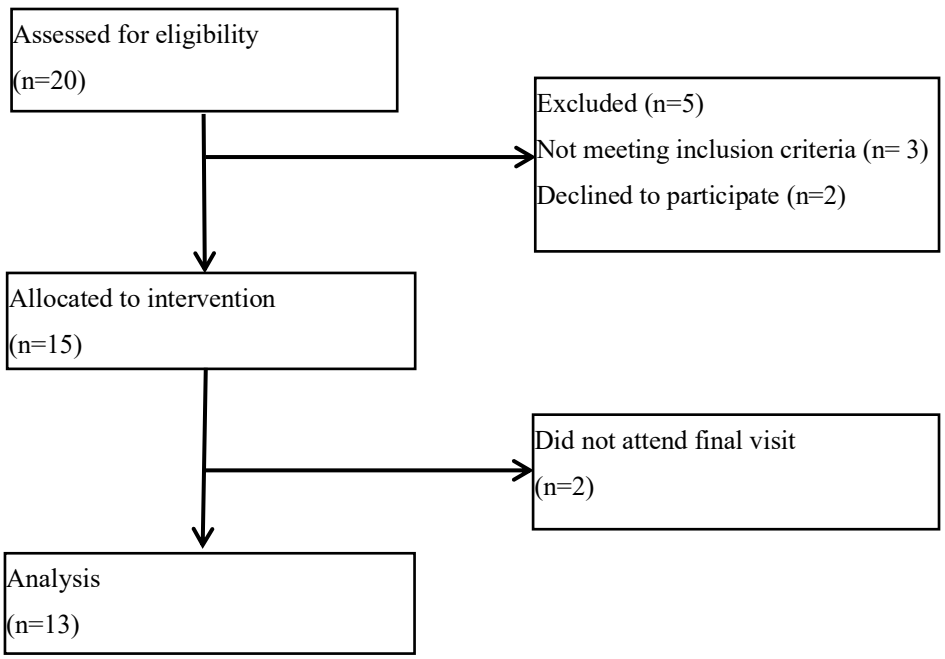



*Figure 5.1 Modified CONSORT flow diagram of participants*

## Baseline Characteristics

*Table 5.2 Baseline characteristics of participants*

| Patient Number | Age (years) | Sex (M/F) | Employment Status | Educational Status | Treatment | Has Partner? (Y/N) | Weight (Kg) | Height (m) |
|---|---|---|---|---|---|---|---|---|
| **1** | 49 | M | Employed | Intermediate | PCI | Y | 71 | 1.74 |
| **2** | 61 | M | Employed | Low | PCI | Y | 117 | 1.75 |
| **3** | 59 | M | Employed | Low | PCI | Y | 91 | 1.80 |
| **4** | 74 | M | Unemployed | Low | PCI | Y | 72 | 1.80 |
| **5** | 70 | F | Unemployed | Intermediate | PCI | Y | 91 | 1.63 |
| **6** | 76 | M | Unemployed | High | PCI | Y | 70 | 1.80 |
| **7** | 77 | M | Unemployed | High | CABG | Y | 73 | 1.84 |
| **8** | 68 | M | Employed | Intermediate | PCI | Y | 98 | 1.81 |
| **9** | 77 | M | Unemployed | Intermediate | PCI | Y | 92 | 1.79 |
| **10** | 55 | F | Employed | High | PCI | Y | 84 | 1.62 |
| **11** | 77 | M | Unemployed | Intermediate | PCI | Y | 106 | 1.80 |
| **12** | 58 | M | Employed | Low | No revascularisation | Y | 119 | 1.80 |
| **13** | 65 | M | Employed | High | No revascularisation | Y | 84 | 1.85 |
| **14** | 51 | F | Employed | Intermediate | CABG | Y | 94 | 1.70 |
| **15** | 60 | M | Employed | High | PCI | Y | 92 | 1.75 |

Phase I of the study recruited 15 patients (Table 5.2) aged 49 to 77. Three were female and 12 were male. Two patients were post coronary artery bypass grafting surgery, and 13 were post ACS. 6MWT distance data was available for 12 patients. All patients improved their 6MWT

distance following completion of the programme. The mean 6MWT distance improved from 390m (SD = 99m) (initial visit) to 508m (SD = 111m) (final visit), a difference of 118m.

## Physical activity and health-related quality of life

### 6MWT

6MWT distance data was available for 12 patients. All patients improved their 6MWT distance following the completion of the programme (Figure 5.2). The mean 6MWT distance improved from 390m (SD = 99m) (initial visit) to 508m (SD = 111m) (final visit), a difference of 118m.

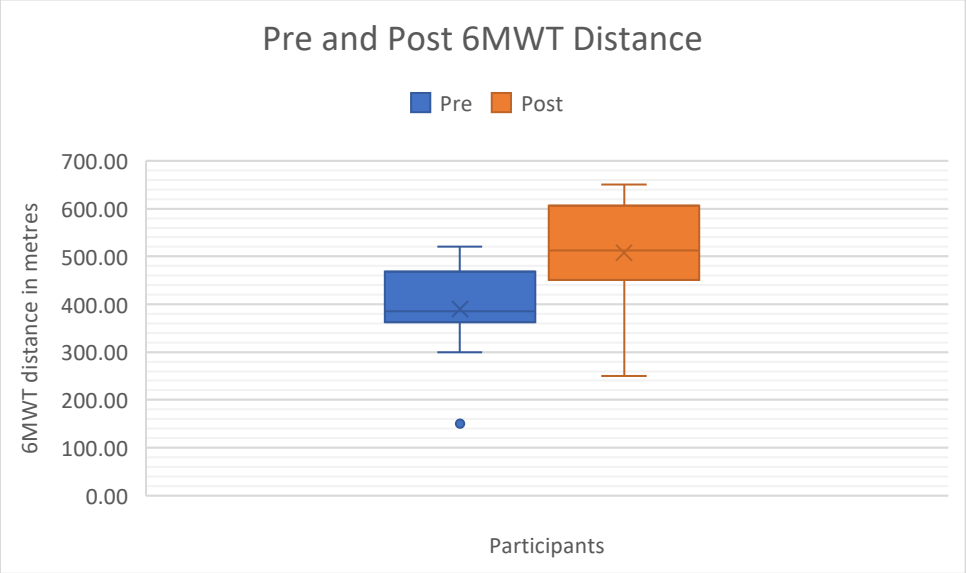



*Figure 5.2 6MWTD pre and post-intervention*

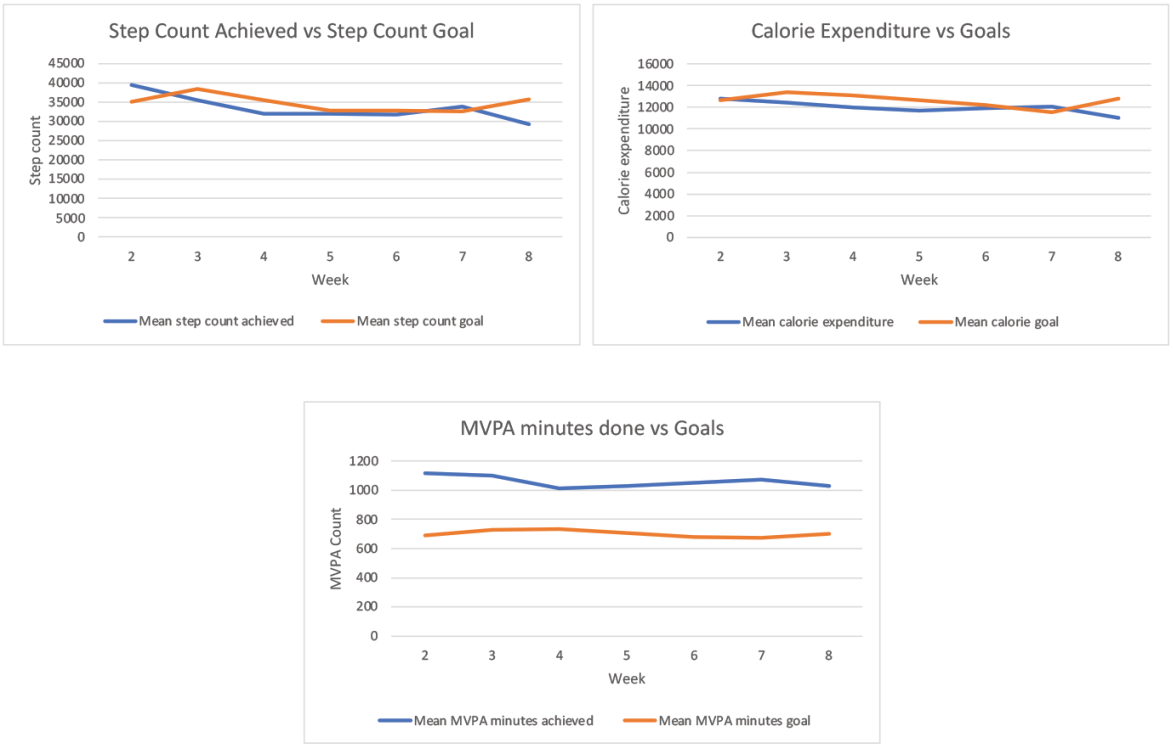



*Figure 5.3 Physical activity achieved vs goals prescribed*

**Step Count**

The highest step count was recorded in week 2 and the lowest in week 8. There was a general decline in the step count achieved over the 8 weeks, with the lowest recorded in the 8th week. Participants exceeded the step count goal on 2 out of the 7 weeks. Despite the general decrease in step count achieved, there was a second peak on week 7, with participants achieving a mean step count of 33933 steps.

**Calorie expenditure**

The mean calorie expenditure decreased over the eight weeks. The highest mean calorie expenditure was 12,782 in week 2, and the lowest was 11,046 in week 8. Most weeks, the mean calorie goal was higher than the mean calorie expenditure.

**MVPA**

The highest MVPA minutes completed (1119) was in week 2, and the lowest was in week 4 (1011). Participants consistently exceeded the MVPA goals across all weeks. MVPA goals followed a similar trend to MVPA minutes completed.

Figure 5.3 illustrates the change in PA goals and counts achieved over the 8 weeks from week 2.

### *Health-related quality of life*

Health-related quality of life questionnaires were completed by 15 participants at the baseline visit and 13 at the final visit.

Following the intervention, there was an improvement in several health-related quality-of-life measures. The EQ-5D-5L index score showed a marginal increase from a mean of 0.80 (SD = 0.15) at baseline to 0.82 (SD = 0.24) at 8 weeks. The VAS score followed a similar pattern, with a mean baseline score of 70.3 and a mean score of 80.4 following the 8 weeks. The mean Barthel index score also increased from baseline following the intervention. The mean Barthel index score also improved following the intervention from a mean of 95.7 to 99.2. The mean clinical frailty index increased following the intervention, reflecting a possible deterioration of the level of frailty from 1.53 to 1.92. However, as with other measures, this is possibly not a true increase, given the overlapping standard deviations and unequal sample sizes. These measures are summarised in Table 5.3.

*Table 5.3 Health-Related Quality of Life Measures Pre and Post-Intervention*

| EQ-5D-5L index score | n | Mean (SD) |
|---|---|---|
| **Baseline** | 15 | 0.8 (0.15) |
| **8 weeks** | 13 | 0.82 (0.24) |
| | | |

| | | |
|---|---|---|
| **EQ-5D-5L VAS** | | |
| **Baseline** | 15 | 70.3 (19.0) |
| **8 weeks** | 13 | 80.4 (14.8) |
| | | |
| **Barthel index** | | |
| **Baseline** | 15 | 95.7 (9.6) |
| **8 weeks** | 13 | 99.2 (2.8) |
| | | |
| **Clinical frailty index** | | |
| **Baseline** | 15 | 1.53 (0.83) |
| **8 weeks** | 13 | 1.92 (0.64) |

**SF36**

SF36 analysis revealed role limitations due to physical health showed the greatest improvement as the mean score increased from 23.3 to 63.5. Energy/Fatigue also improved as the mean score increased from 50.0 to 68.9. The mean emotional well-being score also increased from 73.1 to 82.2. The mean physical functioning and general health scores showed a 2.9-point and 4-point decline. Changes in SF36 domain scores pre and post-intervention are summarised in Table 5.4.

*Table 5.4 SF-36 Domain Scores Pre and Post-Intervention*

| | Intervention Group | |
|---|---|---|
| | Baseline<br>Mean (SD) | 8 weeks<br>Mean (SD) |
| | | |
| **Physical Functioning** | 28.3 (27.3) | 25.4 (25.4) |
| **Role Limitations Due to Physical Health** | 23.3 (37.2) | 63.5 (45.2) |
| **Role Limitations Due to Emotional Problems** | 71.1 (37.5) | 84.6 (32.3) |
| **Energy/Fatigue** | 50.0 (25.2) | 68.9 (23.2) |
| **Emotional Well-being** | 73.1 (19.2) | 82.2 (13.0) |
| **Social Functioning** | 36.0 (13.2) | 42.5 (10.8) |

| | | |
|---|---|---|
| **Pain** | 62.5 (30.7) | 70.4 (31.1) |
| **General Health** | 32.3 (10.5) | 28.3 (12.3) |

**HADS**

HADS score analysis revealed improvements in the levels of both anxiety and depression (Table 5.5). The number of participants classified as "Normal" for anxiety increased from 8 to 11 following the intervention, whilst for depression, there was an increase from 10 to 12.

*Table 5.5 HADS Anxiety and Depression Scores Pre and Post-Intervention*

| | **Intervention Group** | |
|---|---|---|
| | Normal | Borderline/confirmed |
| **HADS Anxiety** | | |
| **Baseline** | 8 (53.3%) | 7 (46.7%) |
| **8 weeks** | 11 (84.6%) | 2 (15.4%) |
| | | |
| **HADS Depression** | | |
| **Baseline** | 10 (66.7%) | 5 (33.3%) |
| **8 weeks** | 12 (92.3%) | 1 (7.7%) |

### 5.3.2 Mobile App usability

**SUS**

System Usability Scale (SUS) scores were available for 12 patients. The mean SUS score for the app was 82 / 100, receiving an overall " Excellent " rating. A meta-analysis of SUS benchmarking for digital health apps concluded a score of 68 (standard deviation 12.5) is suitable for assessing the usability of digital health applications (301).

**MAUQ**

*Table 5.6 MAUQ Domain scoring*

| Domain and Statement | Mean (SD) |
|---|---|
| | |
| The app was easy to use. | 6.50 (0.67) |
| It was easy for me to learn to use the app. | 6.58 (0.67) |
| The navigation was consistent when moving between screens. | 6.67 (0.65) |
| The interface of the app allowed me to use all the functions (such as entering information, responding to reminders, viewing information) offered by the app.. | 5.67 (2.15) |
| Whenever I made a mistake using the app, I could recover easily and quickly. | 4.08 (3.09) |
| I like the interface of the app. | 6.67 (0.78) |
| The information in the app was well organised, so I could easily find the information I needed. | 6.42 (0.90) |
| The app adequately acknowledged and provided information to let me know the progress of my action. | 6.33 (0.89) |
| I feel comfortable using this app in social settings. | 6.58 (0.67) |
| The amount of time involved in using this app has been fitting for me. | 6.50 (0.67) |
| I would use this app again. | 6.25 (1.71) |
| Overall, I am satisfied with this app. | 6.83 (0.39) |
| The app would be useful for my health and well-being. | 6.25 (1.22) |
| The app improved my access to healthcare services. | 5.17 (2.55) |
| The app helped me manage my health effectively. | 6.08 (0.79) |
| This app has all the functions and capabilities I expected it to have. | 5.25 (1.91) |
| I could use the app even when the Internet connection was poor or not available. | 5.67 (1.97) |
| This mHealth app provides an acceptable way to receive healthcare services, such as accessing educational materials, tracking my own activities, and performing self-assessment. | 5.17 (2.52) |

The MAUQ scores demonstrated the mobile app's overall usability (Table 5.6). The highest score was recorded for overall satisfaction with the app (mean value of 6.83/7.00). The lowest score (4.08/7.00) was for the user's ability to recover when they made a mistake. Participants also generally liked the app's interface, with the domain receiving a mean score of 6.67 out of 7.00. They also felt the navigation system was consistent when moving between the screens.

**Analysis of App Analytics (access data)**

App analytical data revealed that each participant spent a mean of 1 minute and 20 seconds each time they opened the app. The average time spent by each participant on the app over the 8 weeks was 1 hour and 1 minute.

The "Goals screen", which displayed the weekly goals for the participant, was viewed the most, with a mean time of 45s, representing 65.2% of the total time spent on the app. The "Summary screen" provided the daily and weekly physical activity level data and was the next most viewed with a mean time spent of 20s. The least time (3s) was spent on the "Home screen", which provided access to other screens.

We did not record any instances of the app stopping unexpectedly during usage.

## Phone calls

We aimed to call each participant every two weeks. However, on certain occasions, we had difficulties contacting them. Each participant was approached for a mean of 3.2 times over the 8 weeks.

Following conversations with the participants, we did not have to alter the goals set by the ML algorithm in any of the instances. As a whole, participants found the goals practical and challenged them to do more safely.

## Retraining the ML model

After completion of Phase I, the ML model was retrained using combined data from the OPTICARE dataset (n=731) and Phase I participants (n=15). Cross-validation of the retrained model yielded $R^2$ values of 0.76 for step count goals and 0.74 for MVPA goals, representing expected decreases from the original model following removal of the target leakage issue.

### 5.3.3 Qualitative Study Results

A total of 15 participants completed phase I of the RECAP trial.

Eight staff members attended the focus groups (5 staff members attended the first focus group, and 3 attended the second)(Figure 5.4). They included specialist CR physiotherapists, nurses, healthcare assistants and administrators with varying levels of experience from 2 years to over 10 years.

7 semi-structured participant interviews were conducted (ranging from 15 to 70 minutes). Participant baseline characteristics are shown in Table 5.7. Although eight patients were invited, one was unable to attend the interview due to personal commitments.

The first staff focus group lasted 45 minutes and the second 90 minutes. Two focus groups took place to enable as many staff members to attend as possible. Staff focus groups took

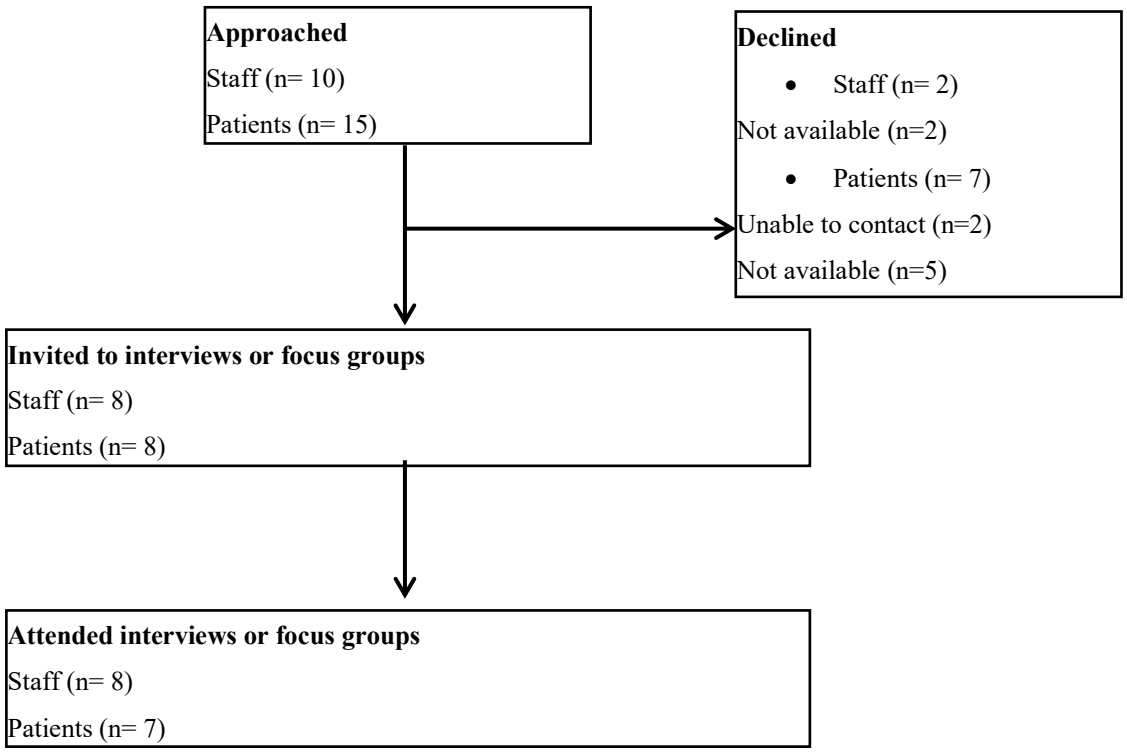



*Figure 5.4 Qualitative study patient recruitment flow diagram*

place after all the patients had completed the intervention. There was no requirement to conduct repeat focus groups as we had reached information power (302, 303).

*Table 5.7 Baseline characteristics of participants who took part in the qualitative study*

| Characteristic | n = 7 |
|---|---|
| Sex; Female | 2 (28.6%) |
| Age; y | 66.6 (8.9) |
| Partner status: with partner | 7 (100.0%) |
| Education level | |
| Low | 2 (28.6%) |
| Intermediate | 4 (57.1%) |
| High | 1 (14.3%) |
| Type of procedure | |
| CABG | 2 (28.6%) |
| PCI | 3 (42.9%) |
| Medical management | 2 (28.6%) |
| Initial 6MWT; m | 387.9 (107.6) |

Note: Data presented as n (%) for categorical variables and mean (SD) for continuous variables. CABG = Coronary Artery Bypass Graft; PCI = Percutaneous Coronary Intervention; 6MWT = Six-Minute Walk Test

Five themes were identified following analysis. First, a digital guardian describes how participants felt while they were taking part in the programme, as knowing they would be remotely monitored gave them a sense of reassurance. Second, targets drive change and

express how they felt motivated by having goals to work towards. Third, the human touch in digital health highlights the impact the routine phone calls by the CR team had on the participants. Fourth, technology made simple emphasises how they felt the mobile app was easy to use and offered them what they expected of the programme. Fifth, convenience meet recovery explains how participants thought the intervention offered them a convenient option to take part in CR.

**A Digital Guardian**

The accelerometers reassured the participants that they were being monitored, and one person was very reluctant to return the device. *"And possibly if I'd still have had the watch on, I would have been able to see that my heart was all right"* (participant 7*)*. It was seen as a safety measure as one patient stated, *"It was encouraging to know that there was somebody in the background who was taking an eye on it"* (participant 4). During the intervention, participants were regularly monitored by staff based at the hospital using the web portal. Participants were made aware of this during the initial visit, and they generally felt safer knowing they were being monitored. *"If anything goes wrong, they're going to know."* (participant 3). Patients also felt that following the programme significantly increased their activity levels as they felt safer exercising, knowing they were being monitored. *"I'm like a spring chicken. My husband says he can't keep up with me"* (participant 7).

On the other hand, staff members preferred hospital-based traditional exercise classes "proven to reduce readmissions" and the "important thing about our exercise our class is we push them into high intensities than they would do at home on their own". "We're always going to be biased because we're a [cardiac rehabilitation team], and that's our job. That's what we do". They expressed fears that AI may take over their roles and the impact it may have on their careers in the long term. "We don't want artificial intelligence taken over a role, and we know through personal experience and our acquisitor that that it works and it's beneficial for patients."

**Targets driving change**

Most participants felt the goals pushed them to do more while being practical. *"I always hit the targets every time, no problem. So, none of the targets were a problem"* (participant 3). One participant stated that the PA goal was a *"real encouragement to keep doing the exercise[s]"* (participant 4). *"It sets targets, and if you got to set targets, then motivate you to meet those targets"* (participant 5). It was the first time that the AI-powered algorithm was tested on real participants. So, we also wanted to find out if the goals were realistic for the participants. Some participants were already physically active before starting the CR programme and found it easier to stay motivated and achieve the PA goals. *"I've always been into exercise and fitness myself from all my life. So, I knew exactly what to do"* (participant 5). Having the goals on their phone meant they could easily access them regularly, even without an internet connection. Most participants would constantly check their apps to see how much of their goals they have achieved. *"So, this week I've only done so many steps, so I need to up my game on the steps. And you can focus on doing the steps"* (participant 1).

Staff echoed the findings from the participant interviews as they felt those who were already into fitness or were used to using an accelerometer such as Fitbit or the Apple watch *"were already very motivated as they were used to using their own technology and they motivated themselves"*. Another staff member felt that the AI algorithm prescribed *"reasonable goals for that patient who's very interested in being independent and walking. It works for them"*. Despite the initial fear about AI replacing their jobs, one staff member felt that *"if the AI algorithm can actually prescribe sensible goals, it would essentially sort of take away that human component"*.

**A Human Touch in Digital Health**

Participants generally viewed the two-weekly HCP contact as a benefit. They found it "encouraging to know that there was somebody in the background who was taking an eye on it" (participant 4). "So, when the rehabilitation team formed, I was like, well, I'm disappointed because I haven't done this... And it was just, it was quite good, it was helpful" (participant 1). It also gave them a sense of reassurance. "Especially when everyone kept ringing up and saying, you know, how are you feeling? And if I felt a bit sort of scared or anything, then I could talk it over with someone" (participant 7).

Staff members felt that some participants tended to have a very long conversation with the physiotherapist during the phone calls as they didn't get the opportunity to answer questions in traditional hospital-based classes. *"I think that because… when they come to the class, they get questions answered all the time. But when we were on the phone [to them], they saved everything up for [us]".* Furthermore, staff felt that some participants may have benefited more from traditional hospital-based classes. *"And I do feel that sometimes patients do need to have face to face".* They also felt that regular phone calls may not be cost-effective if they form part of the CR programme. *"But if you're looking at it in terms of cost-effectiveness, [when] they come to a class, it is spending two hours, but you've got 10 people there [to ask questions in those two hours instead of doing it individually]".*

**Technology made simple**

Participants generally felt the app was easy to use and that it wasn't unnecessarily complex. *"And I thought it was easy to use the app". "No, the app was fine, the app was brilliant"* (participant 1). Even participants who were not very good with technology had no issues using the app. *"I mean, now I'm not really [good] with computers or anything like that, but I found the app quite easy to use"* (participant 3). This was reflected in staff focus groups as they felt participants enjoyed using the app. *"I think they enjoyed using the app".*

Participants had issues with the data from the accelerometer not being automatically uploaded to the online database. This was reflected in several of the interviews. *"I think I did find that I needed to get into the habit of syncing it every day. We were on the way to do it automatically. That was probably my impatience to find out"* (participant 4). Due to the synchronisation delay, participants sometimes felt that the system did not record their PA levels accurately. *"[It] didn't record the amount of steps and stuff like that, that I was doing, that was quite well, but [apart] from that, it was okay"* (participant 2). Staff also felt that the delay in the upload of PA data was reflected in the web portal. *"I found it a little bit often. I'd look on the web portal, and it would say, like, we've got three crosses in a week. And then I'd speak to the patient, and they'd be like, Oh yes, I achieved all the goals".*

Patients had mixed feelings about wearing the accelerometer on their wrists. "Suppose it's just like wearing a watch once you, once you, once you've got it on, I wear it all the time. I don't take, like, my watch. I never take my watch off. So, once you get used to it being there, you just forget about it" (participant 5). There were some individuals who didn't like how the accelerometer felt on their wrist. "I mean, sometimes you'd feel like it was too tight", "It was huge, because you didn't use to wear it in normal watches" (participant 3). "It was good to get the watch off my hand" (participant 1). One female participant felt the watch, which did not have customisation options, did not suit a lady. "The only thing that I would say was the size of the watch itself. Especially for a lady. I mean, it was more like wearing a man's watch" (participant 7). As some participants were already using smart watches, including Fitbit and Apple watches, staff felt that "obviously a feature in the future will be to be able to link it to a Fitbit or an Apple Watch", as some participants "thought that the watches were cumbersome".

Some individuals wanted the option to view data in the form of a table as well as a graph and wanted the option to view their data from the day they started the programme. *"I know it is a minor thing, but it is nice to see how much I have done in numbers as well like in rows and columns"* (participant 1). *"May have been nice to see how much I have done from the very start"* (participant 2). One participant also stated they couldn't view the exercise videos on the mobile app in full-screen mode and preferred it if that was an option.

Staff found the web portal usable overall. However, in the current version of the web portal, there was only one user account through which all staff could log in. Staff felt having separate accounts for each user would make it easier to track and audit what changes have been made and by whom. *"It'd be nice if each of us had our own login, so we know who has made which changes if that makes sense"*.

**Convenience meets recovery**

Most patients were generally very satisfied with the programme as a whole, and all the participants stated that they would recommend it to others. *"I enjoyed it"* (participant 1). *"I would definitely recommend it to anybody really"* (participant 1). Several participants stated

they had no *"complaints at all"* (participant 4). Staff also felt that the mobile app-facilitated home-based CR programme would be a useful addition to their current offerings. *"I think it's a really, if it, if it works, well, it's a really good sort of thing to have in our toolkit for patients".* They also felt that traditional CR programmes offer much more than exercise, and currently, the mobile app-based programme lacked the educational component. *"Think the only thing I'd say is like the fact that they don't get the education, which is a massive part of the program".* As a result, some staff members thought that a hybrid approach might combine the best parts of both programmes. *"Definitely, I think it's got massive potential for a hybrid style of it".*

One of the main benefits of the home-based programme was the convenience as they didn't have to visit the hospital for the CR sessions. *"So essentially, I think the main factor was the transport because you didn't have to keep, you know, going back and forth to the hospital"* (participant 1). *"It was a fact that it may not be a very serious point. It was because I lived some distance from the hospital"* (participant 4). Staff also felt that as participants may have resumed work following their discharge from the hospital and it may not always be possible to find the time to attend hospital-based classes, a home-based programme offered a good alternative. *"Patients who can't attend class for whatever reason, are they back to work. I think it's a very positive it can be a very positive thing". "I do understand people have work commitments, and they can't always attend".*

Some participants also felt that exercise classes didn't suit them, and they preferred to exercise on their own. "*My type of personality is not great in classes and that sort of thing*" (participant 4). Individuals also took part in the study with the intention of helping the hospital and the department with research. *"I just found it was a little bit of a payback to the hospital, and to the people who say, you know, thanks for saving my life, and this is the payback"* (participant 3). *"I suppose that as an individual, I think it's useful and important to support a study"* (participant 5).

Staff members were generally excited about the prospect of having a home-based programme. "But it's quite inspiring, the fact that you're making that for us, and we'll be able to use it, and there's potential for it to be very useful".

Staff felt excited about the possibility of being able to offer a home-based CR programme to their patients. *"And I felt excited. It's a new venture. It's something different for cardiac rehab"*. They stated they have trialled commercial mobile app-based CR programmes in the department previously, but *"none of them worked, and patients didn't like them"*. This was in contrast to the reviews participants gave about the RECAP mobile app.

## Adaptations to the Intervention and Technology

Qualitative interviews highlighted several areas where the mobile app and the web portal could be improved further.

Some participants experienced issues with the accelerometers not synchronising automatically. *"I thought the app didn't always show up how much I did really"*. Another stated, "*I had to manually keep on pressing the sync button*". They also felt it would have been useful if the programme offered them the option to link their own smartwatches to the app. "*I mean, I use my Fitbit. May be nice to connect to that*". A staff member also echoed this view they felt "*As some of our patients use Apple Watch and all that, maybe you could have a feature where they can just connect it to the app*".

Some individuals stated that they would also like the option to view their PA levels in the form of a table, as well as a graph. "*At times, I struggled reading from the chart like, I thought something like rows and columns may be better*".

Another individual stated that they preferred to watch the full screen exercise video on the app. However, at times, the full-screen feature didn't function as expected. "*My eyesight isn't the best. I like watching those workout videos on the whole screen, but I know I pressed that little button in the corner, but occasionally, it wouldn't work*".

During the initial visit, participants struggled to install the app if they had an older version of a smartphone. "*I remember we initially struggled to get the app onto my phone, but I am glad we did*". This was due to an issue with the app not being compatible with older operating systems.

One individual stated he had difficulties accessing the exercise diary and the mood tracker on the app as they weren't always sure where this feature was located. "*I like recording what I do, but some days I just forget, you know, how to open the diary and mood recording page and all that*".

Staff members felt that calling participants every two weeks can be challenging as they didn't answer their phones on some occasions. This meant, staff spent time trying to contact them without being able to speak to them. "*It's a job getting an answer from some patients to be honest. I felt it may be a hindrance to them at times as some of them knew what they were doing*". Staff also stated they would like their user accounts to access the web-portal and for the system to record what changes they have made under that account as it would make it easier to monitor. "*The web-portal is very handy but can we get our personal accounts so it may even record what we are actually doing if that's possible*". They further emphasised that they "*find it confusing how to work out if a patient has actually achieved their exercise targets or not. I find the tick and cross thing a bit all over the place. Maybe it's a hospital computer thing*".

## 5.4 Discussion

In phase I of the study, we tested the usability of a mobile app aimed at delivering home-based CR.

Even though the study wasn't powered to determine the effectiveness of the home-based CR programme, participants improved their 6MWT distance by a mean of 118m. A meta-analysis looking at the effects of outpatient CR on the 6MWT distance found that patients improved their 6MWT distance by 60.43m (95% confidence interval 54.57 to 66.30m; $P<0.001$) (304).

The physical activity goals prescribed by the AI algorithm underwent regular review by the first author and a CR physiotherapist, with the option to override them if deemed unrealistic. However, throughout this study, such intervention was deemed unnecessary.

Only 20% of the patients who took part in the study were females. The study's limited representation of female participants closely mirrors the demographic proportion of females who participated in a CR programme in the year 2021. According to the National Audit of Cardiac Rehabilitation (NACR) quality and outcomes report 2022, 25.9% of females attended a group-based programme, and 28.2% attended a home-based CR programme in 2021 (305).

The recruitment pace within this study has proven to be slower than anticipated, primarily attributable to cancellations of CR clinics, directly impacting patient enrolment. Clinic cancellations have frequently resulted in the postponement of patient appointments due to staff unavailability. This issue has extended beyond the confines of this study and has been observed across the broader NHS. According to the NACR Quality and Outcomes Report 2022, 65% of CR programmes experienced staff loss due to changing jobs and long-term sickness (305).

The app was well received by the participants. Both cardiac rehabilitation delivery staff and study participants agreed that the app was easy to use, and all participants stated they would take part in the programme again or recommend it to others. To the best of our knowledge, this is the first study to use an ML algorithm to prescribe physical activity goals to CR participants in the NHS.

Results from the qualitative study reflect the findings from the main study, which was that the mobile app was usable and was well received by the participants. Even those who were not skilled with technology could easily use the app without any instructions or training. Participants and staff were very satisfied with the mobile app; all participants stated they would recommend it to others. However, they expressed dissatisfaction with the length of time the accelerometers took to synchronise with their mobile apps. This was the most significant finding from this sub-study, which could have a potential impact on participant’s adherence to the programme as well as their satisfaction. This led to some participants feeling that the accelerometers sometimes didn’t track their PA levels.

One of the main motivators for participants participating in the study was their interest in being monitored at home. They felt it provided them with an ongoing link to the hospital.

Mobile app-based programmes associated with monitoring can reduce hospital readmissions while improving patient satisfaction (306). The RECAP mobile app could monitor participants' PA levels but could not monitor their vital signs.

The preliminary ML model (discussed in Chapter 3) had several limitations, including target leakage due to how the perception feature was engineered. In this study, participants' perception of their PA was collected on a week-by-week basis. This allowed the ML model to be retrained again on data that did not have any target leakage. Participants' true weekly performance data was available, which also meant that week 1 performance data didn't have to be feature-engineered. The model was retrained using the data from the Opticare dataset and phase I combined. The problematic perception feature cause target leakage was removed from the Opticare dataset.

This study had several strengths. Firstly, it was guided by a theoretical framework, the NPT. This allowed us to explore how this novel intervention would integrate into real-world clinical practice whilst taking into account the viewpoints of both patients and staff. However, there was potential for selection bias as consecutive sampling was used to recruit patients, and motivated participants may have been more likely to consent to participate. The lead researcher (PW) was also known to the staff, which may have introduced researcher bias.

## Learnings from the Qualitative Study

This study aimed to improve the mobile app and web portal prior to using them in the RECAP feasibility RCT. We identified the following areas that need addressing:

1. Accelerometer synchronisation times

As Actigraph software was a third-party software, we could not investigate its programming code or change it. This was also an issue identified during the alpha testing stage of the intervention. Actigraph was contacted about this issue. However, due to the nature of their

software, a faster automatic synchronisation time could not be achieved. It was still possible for users to manually synchronise it.

As a result, participants will be advised of this during the initial visit. Hence, they are aware of how to manually synchronise their accelerometer devices, particularly if they wish to view their PA levels immediately. We also implemented an automatic notification triggering participants to synchronise their accelerometers.

2. Integration with other smartwatches

Several participants and staff commented about the possibility of integrating different types of smartwatches with accelerometer capabilities, including Fitbit and Apple Watch. This would allow more customisable designs, and participants who already own and use one of these devices regularly would be able to continue using them.

However, integrating different smartwatches would compromise data comparability, so no changes were made in this aspect. RECAP RCT will continue to use the Actigraph accelerometer devices.

3. Viewing the previous week's PA data both in graph and table format

Participants wanted to view their PA data as a graph and a table from the day they commenced the programme. This was primarily because it wasn't always easy to read the exact PA counts from the graph. Following these suggestions, we updated the app to allow users to view their PA data from day one in the form of a graph and a Table.

4. Viewing exercise videos in full-screen mode

Some individuals found that they had difficulties opening the exercise videos available via the mobile app in full-screen mode. As a result, they couldn't always view the content clearly. Following this feedback, an issue was identified relating to the plug-in used to display videos via the app. This was addressed subsequently.

5. App load times were slow on older devices

Participants with older versions of smartphones experienced difficulties installing or opening the app. Since identifying this issue, we have updated the code-based version of the app to enable it to be installed on earlier models of smartphones.

6. It was difficult to access the app-based exercise diary and mood tracker

Some individuals felt they had difficulty accessing or locating the app-based exercise diary and mood tracker. Following the feedback, we have highlighted the area in the app that contains these features so they can be easily located.

7. Phone calls to participants

Most participants generally found the phone calls helpful, while some were already aware of the requirements of the home-based programme and were happy to continue without any further input. Staff focus groups revealed that, at times, it can be difficult to get in touch with some participants due to their availability, and one phone call could take more than 30 minutes. The phone calls were intended to act as a safety net as it was the first time AI was used to prescribe exercises for cardiac patients. It also allowed participants to ask any questions about the technology. Instead, they would be given a contact number to reach the department or the research team if they have any questions. All the PA goals prescribed by the ML algorithm continued to be regularly monitored by an HCP.

8. The web portal has been updated so each user can have their account to login

The web portal was updated to enable users to create their own accounts. During the account creation process, staff members must enter a “security key”. This prevents anyone not affiliated with the CR department and related to the study from accessing the web portal and viewing potentially sensitive participant data. The system will also track any changes that have been made via each user account, including any PA goals that have been amended and any notifications that have been sent.

Following findings from Phase I of the study, several changes were made to the mobile app and the programme as outlined. Phase II of the study aimed to evaluate the feasibility of conducting a larger RCT to assess the effectiveness of the home-based CR programme.

9. Formatting of the web portal rows and columns

Staff felt that, at times, it was unclear whether a participant had achieved their PA goals due to how ticks or crosses were displayed to illustrate this. Following these comments, the web portal was updated to highlight the participants' achievement of their goals.

*Table 5.8 Issues Identified and Changes Made*

| Problem Domain | Problem Identified | Participant/Staff Quotes | Changes Made |
|---|---|---|---|
| **Accelerometer Synchronisation** | Accelerometers not synchronising automatically; manual synchronisation required | "I thought the app didn't always show up how much I did, really."<br>"I had to manually keep on pressing the sync button." | • Participants were advised about manual synchronisation during the initial visit<br>• Implemented automatic notification to remind participants to synchronise accelerometers |
| **Smartwatch Integration** | Participants wanted to integrate personal devices (Fitbit, Apple Watch) | "I mean, I use my Fitbit. May be nice to connect to that"<br>"Maybe you could have a feature where they can just connect it to the app." | **No changes made** - would compromise data comparability; continued using Actigraph accelerometer devices |
| **App Data Viewing Format** | Participants wanted to view PA data in both graph and table format from day one | "At times, I struggled reading from the chart like, I thought something like rows and columns may be better." | Updated app to allow users to view PA data from day one in both graph and table format |

| | | | |
|---|---|---|---|
| **App Video Display** | Difficulties viewing exercise videos in full-screen mode | "My eyesight isn't the best. I like watching those workout videos on the whole screen, but I know I pressed that little button in the corner, but occasionally, it wouldn't work." | Identified and addressed the issue with the video display plug-in |
| **App Device Compatibility** | App installation problems on older smartphones | "I remember we initially struggled to get the app onto my phone, but I am glad we did." | Updated codebase to enable app installation on earlier smartphone models |
| **App Navigation** | Difficulty accessing exercise diary and mood tracker features | "I like recording what I do, but some days I just forget, you know, how to open the diary and mood recording page and all that." | Highlighted the area in the app containing exercise diary and mood tracker features for easy location |
| **Phone Call System** | Bi-weekly phone calls were challenging due to participant availability and time consumption | "It's a job getting an answer from some patients, to be honest. I felt it may be a hindrance to them at times as some of them knew what they were doing." | Replaced regular phone calls with contact numbers for participants to reach the department/research team when needed |
| **Web Portal Access** | Need for individual staff user accounts with tracking capabilities | "The web portal is very handy but can we get our personal accounts so it may even record what we are actually doing, if that's possible" | • Updated web portal to enable individual user accounts<br>• Added security key requirement during account creation<br>• System now tracks changes made by each user account |
| **Goal Achievement Display on Web Portal** | Unclear visual indicators for participant goal achievement | "I find it confusing how to work out if a patient has actually achieved their exercise targets or not. I find the tick and cross thing a bit all over the place." | Updated web portal formatting to better highlight participant goal achievement |

## 5.5 Conclusion

The mobile app was usable, and it was not necessary to manually amend the goals prescribed by the ML algorithm. The mean 6MWT distance improved following the intervention. The mobile app was appropriate for use in a feasibility RCT.

Qualitative data revealed that the mobile app and intervention were well received. The PA goals prescribed by the AI algorithm were also well received and motivated individuals to be more physically active. We identified several areas that could improve the participants' experience, including allowing more options to view their PA data and fixing an error with the built-in video player that displayed exercise videos.

# CHAPTER 6

# 6. RECAP Trial (Phase II) : Results from the Feasibility Randomised Controlled Trial

## Key Learning Points from this Chapter

- The feasibility RCT exceeded all pre-defined targets: 85% recruitment, 100% randomisation, 86% retention, and 92% weekly app adherence rates.

- The mobile application achieved excellent usability (SUS score 82.5/100), and participants rated it highly across multiple domains of the MAUQ questionnaire.

RECAP Trial (Phase II) : Results from the Feasibility Randomised Controlled Trial

- Both intervention and control groups improved the 6-minute walk test distance, with the intervention arm showing improvements in quality-of-life measures.

- No adverse events were reported, and the machine learning algorithm required no manual goal adjustments by healthcare professionals throughout the study.

- Qualitative data confirmed strong feasibility for trial delivery, with participants valuing the convenience and monitoring aspects of the home-based programme.

## 6.1 Introduction

Cardiovascular disease (CVD) continues to be the leading cause of death worldwide, with an estimated 17.9 million deaths in 2019, representing 32% of all deaths globally (94).

A multinational, prospective cohort study found that approximately 70% of CVD cases and deaths were attributable to modifiable risk factors, including physical activity (307). A meta-analysis of the association between physical activity and all-cause and CVD mortality in patients with diabetes demonstrated that physical activity reduced all-cause (Risk ratio (RR) 0.57, 95% confidence interval (CI) 0.49–0.67) and CVD mortality (RR 0.55, 95% CI 0.34–0.68) (308). A prospective study of UK Biobank participants revealed that physical activity reduced all-cause (hazard ratio ranged from 0.85 (95% CI: 0.80 to 0.89) to 0.88 (95% CI: 0.84 to 0.93)) and CVD mortality (hazard ratio ranged from 0.75 (95% CI: 0.68 to 0.83) to 0.90 (95% CI: 0.80 to 1.02)) (309).

A meta-analysis of exercise-based cardiac rehabilitation (CR) for coronary heart disease determined that participation in an exercise-based CR programme reduced CVD mortality [ RR: 0.74, 95% CI 0.64-0.86, number needed to treat (NNT): 37], recurrent cardiac events (RR: 0.82, 95% CI: 0.70-0.96, NNT: 100), and hospitalisations (RR: 0.77, 95% CI: 0.67-0.89, NNT: 37) (19). Despite its benefits, the uptake of CR is low worldwide. In a scoping review which analysed 23 studies, most of the CR programmes had a low participation rate of less than 50% (31). Transport problems and travel time are often cited as the most common barriers to CR participation. This was especially the case for patients living in rural areas (31). Previous studies have found that travel time predicted CR participation, as patients were more likely to attend if the CR programme was closer to their homes (310). Other barriers to low participation rates include age, comorbidities, lack of social support, and economic status (31).

As a result, NICE guidelines recommend that following a myocardial infarction, all patients should be offered cardiac rehabilitation (97). NICE guidelines advise that healthcare professionals offer this in a choice of venues and times (for example, after work) that suit them (97). It also states that CR should be offered at the patient's home if feasible, and

discussions with patients about any factors that may stop them from attending a CR programme should be part of routine care. The guidelines state the CR programme should start within ten days of discharge from the hospital following the admission for acute coronary syndrome (97).

Smartphone-assisted home-based CR programmes may be an alternative to standard hospital-based CR. A meta-analysis of smartphone-assisted CR programmes' effectiveness found that they can significantly improve exercise capacity and treatment compliance (311). Another meta-analysis of behavioural change techniques and intervention characteristics in digital CR found that self-monitoring and feedback on behaviour, information about health consequences, prompts/cues, and goal setting were frequently used by CR programmes (312).

We developed a mobile app powered by AI that could prescribe participants weekly physical activity goals as part of a home-based CR programme and a web portal for CR staff to remotely monitor participants. To the best of our knowledge, no other mobile apps could automatically prescribe PA goals using AI, as part of a remote CR programme. We developed a machine learning (ML) algorithm that could prescribe weekly physical activity goals (in step count, calorie count, and moderate-to-vigorous physical activity minutes) to study participants.

Moving the CR programme from the hospital setting to the home setting may make it more accessible for the patients and allow hospitals to accommodate more patients at any given time, reducing waiting times. It also aligns with the long-term NHS goals of making services digital (101).

The RECAP feasibility trial aimed to answer the following research questions:

- Is it feasible to carry out a large, definitive RCT to determine the clinical and cost-effectiveness of a tailored home-based rehabilitation programme facilitated by an AI-enabled app?
- Is usability and user satisfaction of the AI-powered mobile app acceptable?

## 6.2 Methods

The trial protocol (Appendix D) has been previously published (1).

### 6.2.1 Study design and randomization

The RECAP trial was a single-centre feasibility RCT. Potentially eligible participants were identified by the clinical team. They were given participant information sheets (Appendix F) before discharge or contacted via phone before their initial appointment with the CR department for pre-screening. After discussion, those wishing to participate provided written informed consent before confirming eligibility and baseline assessments (Appendix E).

Eligible and consenting participants were randomly allocated 1:1 to the home-based CR (intervention) programme or the standard hospital-based rehabilitation classes (control).

Trial randomisation to the two arms was conducted using Castor, an online randomization tool (https://www.castoredc.com), in a 1:1 ratio using stratification, based on the treatment a participant had received: surgical (e.g., coronary artery bypass graft surgery) versus non-surgical (e.g., percutaneous coronary intervention). It was not possible to blind participants or the assessors to the allocation due to the nature of the intervention. The staff members who conducted the CR classes as part of standard care also conducted study assessments.

### 6.2.2 Trial Procedures

#### The intervention

Participants assigned to the intervention arm were advised and guided on how to install the RECAP mobile app onto their phones and were given an accelerometer (Actigraph CentrePoint Insight Watch Activity Monitor). They were advised to wear it continuously on their non-dominant wrist throughout the day. They were given weekly exercise goals

(automatically prescribed by the AI algorithm), which they could view on the mobile app. The accelerometers detected the physical activity levels of each participant, and the data from these devices were uploaded automatically and regularly to remote servers online via the mobile app every 24 hours. The RECAP trial mobile app retrieved this physical activity data, which was then fed automatically onto the ML algorithm informing exercise prescriptions. The ML algorithm also took into account data such as demographics, education level, partner status, goal attainment and participant's perception of exertion to prescribe the PA goals. We used the XG Boost algorithm to generate PA goals for participants (313). CR staff could override these goals if they were deemed inappropriate. The development of the intervention will be discussed in more detail in a separate paper.

Via the mobile app, participants could also view exercise videos (recorded by a physiotherapist based at the hospital) demonstrating exercises done as part of standard care. They were also given a booklet containing exercises. The intensity of the exercises increased every 1-2 weeks and included both aerobic and strength training. If a participant did not want to continue with the intervention, they could switch to standard care at any point in time. Similar to standard care, the home-based CR intervention was eight weeks long.

#### Standard Care

As part of standard care, participants in the standard care arm took part in once weekly hospital-based CR sessions for eight weeks, consisting of formal exercise classes incorporating both aerobic exercises and strength training. Each session was two hours long and conducted by a team of CR nurses and physiotherapists, with up to a maximum of 12 participants in each session.

In addition to this, participants were also advised to exercise at home for up to 45 minutes a day. However, they weren't given access to the mobile app or provided with an accelerometer and weren't remotely monitored, unlike in the intervention arm.

### 6.2.3 Participants and trial assessments

Eligible participants were those who had postcardiac surgery or admission for acute coronary syndrome had been referred for CR, were over the age of 18, had access to an Android or iOS mobile device and were willing to provide informed consent.

We excluded participants who were awaiting urgent surgery, had unstable angina, were pregnant, or were currently enrolled in another interventional clinical trial or study where the intervention was considered likely to impact the outcomes of the RECAP trial.

As part of standard care, patients were invited for a preassessment clinic appointment following their discharge from the hospital. The baseline visit for the trial coincided with this appointment to reduce travel for participants. The final visit for the trial took place eight weeks after the baseline visit, following the completion of the CR programme.

During these visits, trial assessments were conducted by members of the research team or the CR team.

## Baseline Visit

Trial assessments were conducted following obtaining consent and before randomisation. The baseline assessments consisted of the 6MWT (291), EuroQOL 5-Dimensions (EQ5D5L) (292) and 36-item Short Form survey (SF36)(V.1.0) (293), Hospital Anxiety and Depression Scale (HADS) (294), Barthel Index (295) and clinical frailty scale (CFS) (Rockwood scale)(296).

The assessments, including the 6MWT, were conducted by CR and the research team members.

## Final Visit

At the final visit, participants in the intervention arm completed the system usability scale (SUS) and the mobile application usability questionnaire (MAUQ) in addition to the

questionnaires they had completed at the baseline visit. We also repeated the 6MWT and observations, including blood pressure and weight.

### 6.2.4 Outcome Measures

The main aim of this RCT was to establish the feasibility of implementing the intervention in the CR setting and to determine if conducting a large-scale RCT is possible. Feasibility was determined by the number of patients recruited to the trial, rate of randomisation, dropout rates, adherence to the intervention and qualitative data. The trial was considered to be feasible if ≥ 70% of patients identified as likely to be eligible consented to take part, ≥ 80% of the patients eligible and consented to randomised, ≤ 20% of patients withdrew after randomisation or switched to the alternative arm, ≥ 75% of patients in the intervention arm used the app weekly and if the delivery of trial was judged to be strongly feasible by qualitative data.

As secondary outcomes, we assessed the impact of the intervention on physical fitness by changes in 6MWTD and physical activity measured by accelerometery, as well as the impact on health-related QOL using QOL scores. Mobile app usability was assessed using the SUS score and the MAUQ.

### 6.2.5 Statistical analysis

As the RECAP trial was a feasibility RCT, we did not perform a formal sample size calculation. We estimated that 70 participants would enable us to answer our research questions, and this sample size would allow us to estimate the standard deviation of continuous outcomes, including the 6MWT distance and allow us to plan a larger RCT (314).

Participant's baseline characteristics were provided as descriptive statistics (mean and standard deviation or median and interquartile range) for continuous variables. Categorical variables are summarised as frequencies and percentages.

The uptake and adherence to the intervention rates were presented as percentages. We analysed the outcomes using an intention-to-treat principle as per the randomisation

regardless of the patient's adherence to the intervention, treatment they received or protocol deviations.

Summary estimates of effects and their confidence intervals are provided. The unadjusted mean difference for continuous outcomes and odds ratios for binary outcomes are provided. This was further adjusted for factors including age and sex as it may have impacted adherence to intervention.

Due to the nature of this RCT, no interim analysis was carried out. A senior statistician with expertise in machine learning oversaw statistical analysis.

### 6.2.6 Ethics

RECAP trial received NHS research ethics approval from the Berkshire research ethics committee in September 2022 (IRAS 315483) (Appendix C). The RCT was registered on the ISRCTN trial database: ISRCTN97352737.

## 6.3 Results

70 patients were planned to be recruited. However, due to the cancellation of CR clinics due to long-term staff absence, limited availability of accelerometers, and time constraints, only 51 patients were recruited between July 2023 and March 2024 (Figure 6.1).

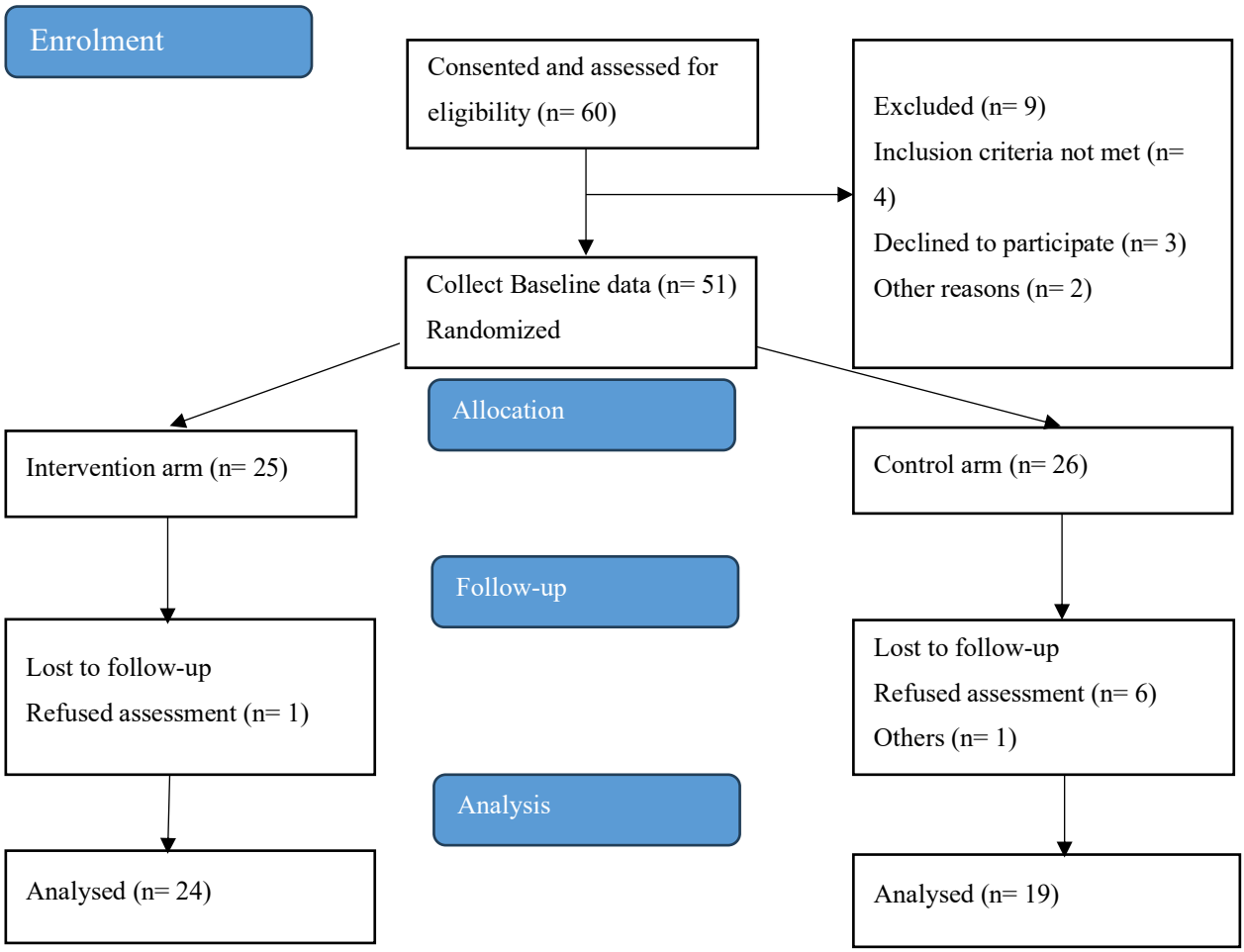



*Figure 6.1 Consolidated Standards of Reporting Trials (CONSORT) flow diagram of participants*

## Baseline Characteristics

Of 51 participants randomised, 26 were in the control arm, and 25 were in the intervention arm. Baseline characteristics were comparable between arms, with mean ages of 62.58 (±8.76) and 65.60 (±8.11) years for control and intervention arms, respectively. Most participants were male (control: n=22; intervention: n=19) and had intermediate educational status (control: n=20; intervention: n=23). A participant was considered to have a low education level when their highest achieved education level was primary school, intermediate level when the highest level of education was secondary school or secondary vocational and high educational level if they have completed higher professional education or university. The most prevalent comorbidities in both arms were hypercholesterolemia (control: n=23; intervention: n=24) and hypertension (control: n=20; intervention: n=23). PCI was the most

common treatment modality between the arms (control: n=13; intervention: n=14). Table 6.1 summarizes the baseline characteristics of participants.

*Table 6.1 Baseline characteristics*

| | **Treatment Arm** | |
|---|---|---|
| | **Control** | **Intervention** |
| | n = 26 | n = 25 |
| Mean age, years (SD) | 62.58 (±8.76) | 65.60 (±8.11) |
| Men (n) | 22 | 19 |
| | | |
| Observations, mean (SD) | | |
| Weight (kg) | 85.95 (±16.44) | 82.53 (±16.68) |
| Height (m) | 1.74 (±0.11) | 1.71 (±0.08) |
| Heart rate (bpm) | 65.12 (±7.64) | 66.72 (±12.36) |
| Systolic (mmHg) | 131.54 (±15.62) | 129.72 (±16.06) |
| Diastolic (mmHg) | 75.23 (±9.13) | 74.80 (±8.96) |
| | | |
| Treatment received (n) | | |
| PCI | 13 | 14 |
| CABG | 6 | 8 |
| No revascularization | 7 | 3 |
| | | |
| Educational Status (n) | | |
| High | 6 | 2 |
| Intermediate | 20 | 23 |
| Low | 0 | 0 |
| | | |
| Has a partner (n) | 23 | 21 |
| | | |
| Comorbidities (n) | | |
| History of MI | 4 | 7 |
| History of angina | 6 | 6 |
| History of PCI | 1 | 2 |

| | | |
|---|---|---|
| Previous CABG | 0 | 1 |
| Previous TIA or stroke | 3 | 1 |
| Family history of cardiac disease | 21 | 17 |
| History of diabetes | 8 | 3 |
| History of hypertension | 20 | 23 |
| History of hypercholesteremia | 23 | 24 |

### 6.3.1 Feasibility outcomes

#### *Recruitment and Dropout Rates*

Between 09th July 2023 and 28th March 2024, we assessed eligibility for 60 patients referred for CR at the James Cook University Hospital and 51 of the participants were found to be eligible and randomised. Out of the nine patients who were not randomised, the most common reason for not proceeding was because they either strictly preferred a home-based programme due to travel restrictions or didn't have access to a compatible mobile phone. All 51 who consented were confirmed eligible and subsequently randomised into either the intervention arm (n=25) or the control arm (n=26). The recruitment and randomization rates were 85%  and 100%, respectively. Figure 1 shows the flow of participants in the trial. No adverse events were recorded.

Out of the 51 randomised participants and started on a rehabilitation programme, 44 participants attended the final visit, indicating a retention rate of 86%. Out of the 7 participants who failed to attend the final visit, 6 were randomly assigned to the control arm. The most common reason for failing to attend is work commitments and transport difficulties. The mean attendance for standard care classes was 5.6 sessions out of 8 (n=26). Participants who didn't attend the final visit had a mean attendance of 2.3 sessions out of 8 (n= 6). Of these 6 participants, 3 didn't attend any of the classes. One patient initially randomised to the intervention switched to the hospital arm after four weeks due to difficulties with the accelerometer synchronization. In the intervention arm, 92% of the participants opened the app weekly, for a mean of 4.2 days per week. Table 6.2 outlines the attainment of the feasibility outcomes.

In the standard care arm, each participant attended a mean of 5.6 (SD = 3.0) hospital-based CR sessions (out of 8). Out of the 26 participants randomised to standard care, 11 attended all of the eight sessions, and four participants didn't attend any session.

Therefore, we conclude this is feasible based on our patient recruitment, randomisation and retention figures.

*Table 6.2 Feasibility Outcome Measures*

| | Go – proceed with RCT | Amend – proceed with changes | Stop – do not proceed unless changes are possible | Outcomes achieved in this RCT |
|---|---|---|---|---|
| Feasibility of patient recruitment | ≥ 70% of approached patients consented | 50 – 70% of approached patients consented | ≤ 50% of approached patients consented | 85% |
| Feasibility of patient randomisation | ≥ 80% of the patients eligible and consented randomised | 50 – 80% of the patients eligible and consented randomised | ≤ 50% of patients eligible and consented randomised | 100% |
| Feasibility of patient retention (at 8 weeks following randomisation) | ≤ 20% of patients dropped out after randomisation | 20 – 50% of patients dropped out after randomisation | ≥ 50% of patients dropped out after randomisation | *86%* |
| Adherence to intervention | ≥ 75% of patients using the app weekly | ≥ 50% of patients using the app weekly | ≤ 50% of patients using the app weekly | 92% |
| Delivery of trial | Delivery of trial judged to be strongly feasible by qualitative data | Delivery of trial judged to be feasible by qualitative data | Delivery of trial judged to be possibly feasible by qualitative data | Qualitative data indicated the delivery of the trial is highly feasible |

### *6-minutes Walk Test Distance*

The mean 6MWT distance increased from 381m at baseline to 446m at follow-up in the hospital arm and 416m to 463m in the intervention arm. While the intervention arm started with a higher mean (a difference of 35m), the median increase was comparable across arms (60m for the intervention arm vs 70m for the hospital arm). However, the control arm demonstrated significantly greater variability, with standard deviations consistently exceeding those of the intervention arm by approximately 30m at both time points (73.6 vs 47.9 at baseline; 114.7 vs 60.8 at follow-up). Table 6.3 and Figure 6.2 show the 6MWT distance comparison of the participants.

*Table 6.3 6MWT distance of participants across the two arms*

| | Control | | Intervention | |
|---|---|---|---|---|
| | Baseline | Follow-up | Baseline | Follow-up |
| Mean (SD) | 381 (74) | 446 (115) | 416(48) | 463(61) |

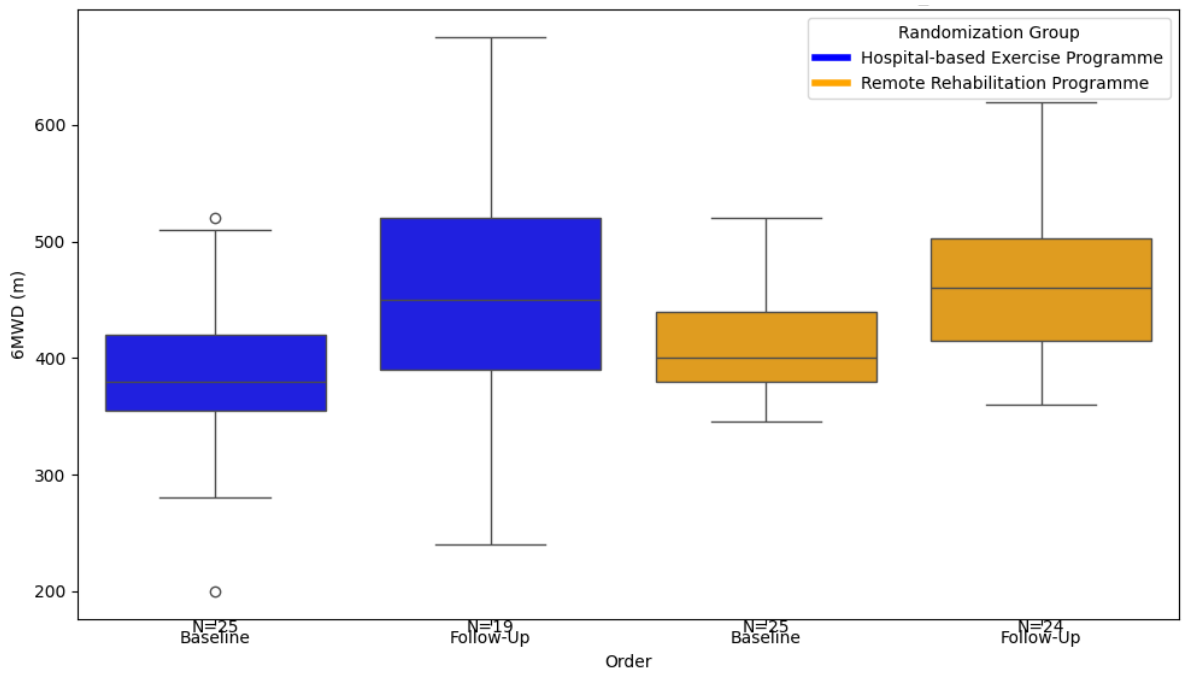



*Figure 6.2 Comparison of 6MWT distance of participants*

We used a longitudinal mixed-effects model to analyse the relationships between age, sex, treatment arm, and 6MWT distance over time. The model coefficients provided estimates of the magnitude and direction of these effects. With increasing age, there was a negative association with 6MWT distance (β = -2.034, 95% CI [-4.374, 0.306]). Sex did not demonstrate a clear effect (β = 21.304, 95% CI [-28.400, 71.008]). While 6MWT distance increased over time across all participants (β = 61.101, 95% CI [35.211, 86.991]), a participant's treatment arm did not affect this rate of change (β = -9.453, 95% CI [-43.187, 24.281]).

### 6.3.2 Physical activity and health-related quality of life

Participants' PA goal attainment compared with the prescribed goals is shown in Figure 6.3.




*Figure 6.3 Physical activity goals achieved vs prescribed for the participants in the intervention arm over the 8 weeks. Week 2 marks the starting point of the graph, as this is when the ML algorithm begins prescribing PA goals.*

**Step Count (intervention arm)**

From week 1 to week 3, there is an increase in the achieved step count, peaking at 52,517 in week 3. However, there is a decline in week 5, where the achieved mean drops to 40,892. During week 8 the step count achieved recovers with an achieved mean of 50,464, though still below the peak of week 3.

**Calorie expenditure (intervention arm)**

Mean daily caloric expenditure ranged from 9832 calories (Week 1) to 11226 calories (Week 8), with standard deviations ranging from 2726 to 4617 calories across the eight weeks. Prescribed caloric expenditure varied from 2000 calories (Week 1) to 12191 calories (Week 4), with standard deviations ranging from 0 to 3829 calories. Although there is some fluctuation, caloric expenditure generally increased across the eight-week study period.

**MVPA (intervention arm)**

Mean MVPA duration ranged from 936 minutes (week 1) to 1115 minutes (week 8), with standard deviations ranging from 409 to 611 minutes across the eight weeks. Prescribed MVPA duration varied from 400 minutes (week 1) to 749 minutes (week 5), with standard deviations ranging from 0 to 193 minutes. While there's fluctuation, a general upward trend in mean MVPA duration is observed.

### 6.3.3 Health-related quality of life

The EQ-5D-5L index scores remained stable in both the intervention and control arms. The intervention arm maintained a mean score of 0.9 (SD=0.1) from baseline to 8 weeks, while the hospital arm had a mean score of 0.8 (SD=0.2). The EQ-5D-5L visual analogue scale score demonstrated significant improvement for the intervention arm after 8 weeks, with the mean score increasing from 75.7 to 83.8, while the hospital arm showed minimal change.

The intervention arm demonstrated significant improvements in HADS scores, with the proportion of patients classified as “normal” increasing from 72% to 95.8% for anxiety and

from 88% to 95.8% for depression after 8 weeks. SF36 analysis revealed the intervention arm showed significant improvements in role limitations due to physical health (increase in mean score from 42.0 to 83.3), social functioning (74.5 to 91.1), and pain (72.0 to 85.0) from baseline to 8 weeks. In contrast, the control arm's scores remained stable or declined.

Barthel index questionnaire assessment demonstrated an improvement in both arms, with the mean (SD) for the intervention arm increasing from 99.8 (3.37) at the baseline visit to 100 (3.33) at the final visit, and the control arm showed an increase from 98.46(3.43) to 98.5 (3.38). The mean clinical frailty index scores increased from 1.33 (0.56) to 1.46 (0.59) for the intervention group and from 1.12 (0.91) to 2.15 (1.04) for the control group.

### *Regression Analysis*

Longitudinal mixed-effects analyses examined potential differences between the home-based intervention and standard hospital care across multiple outcome measures, adjusting for age, sex, time, and time × treatment interactions. The time × treatment interaction effects, representing the differential change from baseline to follow-up between treatment groups, showed patterns across psychological outcomes. For anxiety measured by HADS, the adjusted time × treatment interaction was -3.09 points (95% CI: -4.65, -1.54) favouring the intervention group, while depression scores showed an adjusted interaction effect of -2.43 points (95% CI: -3.50, -1.35)(Table 6.4 and Table 6.5).

*Table 6.4 Analysis of HADS - Anxiety*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | -0.141 | -0.240, -0.042 | 0.006 |
| Sex | | | |
| Male | — | Reference | |
| Female | 1.57 | -0.510, 3.66 | 0.14 |
| Time | | | |
| Initial | — | Reference | |

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Followup | 0.283 | -0.949, 1.51 | 0.65 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | -3.09 | -4.65, -1.54 | <0.001 |

[1]CI = Confidence Interval

*Table 6.5 Analysis of HADS - Depression*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | -0.165 | -0.260, -0.071 | <0.001 |
| Sex | | | |
| Male | — | Reference | |
| Female | 1.60 | -0.404, 3.60 | 0.12 |
| Time | | | |
| Initial | — | Reference | |
| Followup | 0.265 | -0.563, 1.09 | 0.52 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | -2.43 | -3.50, -1.35 | <0.001 |

[1]CI = Confidence Interval

## Quality of Life and Psychological Outcomes

*Table 6.6 SF36 PCS and MCS Descriptive Statistics*

| Characteristic | Hospital group, N = 26 | Remote group, N = 25 | **Overall**, N = 51 |
|---|---|---|---|
| Baseline PCS | | | |
| N | 26 | 25 | 51 |
| Mean (SD) | 48.27 (2.54) | 47.55 (1.66) | 47.91 (2.16) |
| Median (IQR) | 47.22 (46.68, 50.08) | 47.22 (46.76, 48.14) | 47.22 (46.71, 48.89) |
| Range | 44.55 - 55.45 | 44.80 - 52.24 | 44.55 - 55.45 |
| Follow-up PCS | | | |
| N | 20 | 24 | 44 |
| Mean (SD) | 48.59 (2.39) | 47.11 (1.03) | 47.78 (1.91) |
| Median (IQR) | 47.98 (46.91, 49.89) | 46.90 (46.40, 47.65) | 47.39 (46.64, 48.34) |
| Range | 44.94 - 55.57 | 45.65 - 49.48 | 44.94 - 55.57 |
| Baseline MCS | | | |
| N | 26 | 25 | 51 |
| Mean (SD) | 50.4 (6.6) | 52.3 (4.3) | 51.3 (5.6) |
| Median (IQR) | 53.6 (44.9, 55.6) | 52.8 (50.4, 55.9) | 53.2 (48.4, 55.8) |
| Range | 32.6 - 57.5 | 39.9 - 58.0 | 32.6 - 58.0 |
| Follow-up MCS | | | |
| N | 20 | 24 | 44 |
| Mean (SD) | 49.9 (6.3) | 54.4 (3.1) | 52.3 (5.3) |
| Median (IQR) | 51.9 (45.7, 53.3) | 54.7 (53.5, 56.9) | 53.7 (51.1, 56.1) |
| Range | 32.6 - 58.3 | 45.4 - 58.2 | 32.6 - 58.3 |

After adjusting for age and sex, the SF-36 Mental Component Summary showed an adjusted time × treatment interaction of 2.86 points (95% CI: 1.31, 4.41) favouring the intervention group. Role limitations due to emotional problems showed an adjusted interaction effect of 20.6 points (95% CI: 7.87, 33.4). Social functioning showed an adjusted improvement of 20.3 points (95% CI: 10.1, 30.4). The EQ-5D-5L visual analogue scale showed an adjusted time × treatment interaction of 8.12 points (95% CI: 1.43, 14.8). Additional SF-36 domains showing adjusted improvements in the intervention group included vitality with an interaction effect of

9.77 points (95% CI: 0.221, 19.3) and mental health with 8.79 points (95% CI: 3.39, 14.2). Bodily pain scores showed an adjusted improvement of 10.8 points (95% CI: 1.23, 20.4).

## Physical Function Analysis

*Table 6.7 Analysis of 6MWT*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | -1.96 | -4.36, 0.446 | 0.11 |
| Sex | | | |
| Male | — | Reference | |
| Female | -21.0 | -71.7, 29.7 | 0.41 |
| Time | | | |
| Initial | — | Reference | |
| Followup | 62.1 | 35.2, 89.0 | <0.001 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | -10.5 | -45.1, 24.1 | 0.55 |

[1]CI = Confidence Interval

After adjusting for age and sex, the 6MWT showed a minimal adjusted time × treatment interaction (β = -10.5, 95% CI: -45.1, 24.1)(Table 6.7). The SF-36 Physical Component Summary showed an adjusted interaction effect of -0.869 (95% CI: -1.53, -0.207), and the physical functioning subscale showed an adjusted effect of -10.6 points (95% CI: -16.9, -4.19). The SF-36 role physical domain showed an adjusted time × treatment interaction of 36.9 points (95% CI: 18.6, 55.1) favouring the intervention group. The EQ-5D-5L utility scores showed an adjusted interaction effect of 0.057 (95% CI: -0.013, 0.126).ale (β = -10.6, 95% CI: -16.9 to -4.19). These findings may reflect baseline group differences or measurement variability rather than true treatment effects. Conversely, pain scores suggested

improvement (β = 10.8, 95% CI: 1.23 to 20.4), as did vitality (β = 9.77, 95% CI: 0.221 to 19.3). Further regression analysis tables are given in Appendix I.

### 6.3.4 Mobile App usability

Mobile app usability was assessed using the SUS score and the MAUQ. The mean SUS score was 82.5 (n=24), corresponding to an "excellent" score.

The MAUQ assessment yielded predominantly favourable results across multiple dimensions. The app demonstrated strong performance in user onboarding, with participants reporting high scores for ease of learning (M = 6.4, SD = 0.9) and consistency in navigation between screens (M = 6.3, SD = 0.9). However, some aspects showed room for improvement, particularly in healthcare service accessibility (M = 4.8, SD = 1.6) and progress feedback (M = 5.2, SD = 1.7). Table 6.8 shows the MAUQ scores for each domain assessed out of 7, where 1 represents "strongly disagree" and 7 represents "strongly agree".

*Table 6.8 MAUQ scores for each domain*

| Domain and Statement | Mean (SD) |
|---|---|
| | |
| The app was easy to use. | 6.0 (1.1) |
| It was easy for me to learn to use the app. | 6.4 (0.9) |
| The navigation was consistent when moving between screens. | 6.3 (0.9) |
| The interface of the app allowed me to use all the functions (such as entering information, responding to reminders, and viewing information) offered by the app.. | 5.6 (1.5) |
| Whenever I made a mistake using the app, I could recover easily and quickly. | 5.3 (2.0) |
| I like the interface of the app. | 5.9 (1.5) |
| The information in the app was well organized, so I could easily find the information I needed. | 6.1 (1.2) |
| The app adequately acknowledged and provided information to let me know the progress of my action. | 5.2 (1.7) |
| I feel comfortable using this app in social settings. | 6.6 (0.8) |
| The amount of time involved in using this app has been fitting for me. | 6.3 (1.3) |
| I would use this app again. | 5.9 (1.5) |
| Overall, I am satisfied with this app. | 6.2 (1.4) |
| The app would be useful for my health and well-being. | 5.8 (1.3) |

| | |
|---|---|
| The app improved my access to healthcare services. | 4.8 (1.6) |
| The app helped me manage my health effectively. | 5.4 (1.5) |
| This app has all the functions and capabilities I expected it to have. | 6.0 (1.3) |
| I could use the app even when the Internet connection was poor or not available. | 5.4 (1.9) |
| This mHealth app provides an acceptable way to receive healthcare services, such as accessing educational materials, tracking my own activities, and performing self-assessments. | 5.4 (1.5) |

App analytical data revealed that each participant, on average, spent 1 minute and 45 seconds each time they opened the app. The average time spent by each participant on the app over the 8 weeks was 1 hour and 3 minutes.

## 6.4 Discussion

This randomised feasibility study examined the feasibility of conducting a future large-scale RCT to evaluate the effectiveness of an AI-powered home-based CR programme compared to standard care for patients who are post-ACS and cardiac surgery. We assessed this using pre-defined criteria in the domains of recruitment, randomization, retention, and adherence rates, as well as qualitative assessment of the delivery of the trial. The study exceeded all feasibility targets that were set in all the domains, demonstrating that it is feasible to conduct a large-scale RCT. To the best of our knowledge, this was the first feasibility RCT to examine an AI-powered remote CR programme in the NHS using real-time patient PA data.

As secondary outcomes, we aimed to assess the impact of the intervention and standard care on physical fitness as assessed by the 6MWT and health-related quality of life as assessed by questionnaires. As expected, the 6MWT distance increased from baseline to the follow-up visit for both the intervention and standard care arms. Even though our study wasn't powered to assess the efficacy of the intervention, it was able to increase the 6MWT distance by 11% compared to 17% of standard care. However, it is worth noting that the intervention arm had a higher baseline 6MWT distance than the standard care arm (416m vs 381m). The standard care arm also had a higher standard deviation compared to the intervention arm (74 vs 48). The standard care arm also had a higher dropout rate compared to the intervention arm (6 vs 1). Future studies may benefit from stratification based on the baseline fitness levels of participants to allow for a fairer comparison. This may also help reduce the high dropout rate,

which was observed in the standard care arm, especially if incentives could be provided for transport. The missing data may have impacted the 6MWT distance analysis. The 6MWT distance could potentially be a primary outcome to assess the effectiveness of the intervention in a definitive RCT.

The mean EQ-5D-5L VAS score increased from 75.7 at baseline to 83.8 at the final visit for the intervention arm. Participants in the intervention arm also showed a substantial improvement in SF-36 scores over several domains, including role limitations due to physical health and social functioning. The intervention arm also showed an improvement in anxiety levels, with 72% of participants classified as “normal” as baseline, increasing to 95.8% at the follow-up visit. The intervention may be effective in improving health-related quality-of-life measures. However, larger powered studies are needed to further explore this.

Following regression analysis, the intervention arm demonstrated superior outcomes compared to standard care across psychological and quality of life measures. The intervention group showed significant reductions in HADS anxiety (3.09 points) and depression (2.43 points), with substantial improvements in role emotional (20.6 points) and social functioning (20.3 points). The physical function results were mixed. While the 6MWT showed no significant difference between groups ($\beta$ = -10.5, 95% CI: -45.1, 24.1), and some SF-36 physical subscales showed negative interaction effects, the role physical domain improved markedly in the intervention group (36.9 points). This discrepancy between objective physical measures and self-reported physical role function may reflect baseline differences or indicate that home-based participants experienced functional improvements in daily activities despite similar exercise capacity. The intervention group also reported improvements in bodily pain (10.8 points) and vitality (9.77 points). These findings suggest the intervention may be effective in improving patients' quality of life measure, which warrants further investigation.

The trial is a feasibility study, not efficacy as such, wide CIs and $\geq$ 15 outcome tests mean these effects are exploratory. Nevertheless, several estimates exceed published MCIDs (e.g., $\geq$ 20 points on SF-36 domains), indicating potentially meaningful gains.

For the duration of this study, researchers and CR staff based at the hospital had access to a dashboard which allowed them to monitor participants' PA levels, and the goals prescribed for them. They also had the option to modify the goals if they were deemed inappropriate or unacceptable for the participants. However, this wasn't necessary in any of the instances for any of the goals that were prescribed.

The mobile was very usable, receiving a SUS score of 82.5 out of 100. Previous studies have suggested that a score of 70 points is "fully acceptable" (315-317). The MAUQ questionnaire showed participants rated the app high for ease of learning (6.4/7) and social acceptability (6.6/7). However, it ranked lower for progress feedback (5.2/7). Taken together with qualitative data analysis, participants generally found the app to be very usable. However, they were discouraged by the fact that there was a delay in physical activity data being transmitted from the accelerometers to their app. This resulted in some participants being frustrated and may have affected their adherence to the app. Future interventions will need to address this. Qualitative data will be published separately in more detail.

One commonly cited barrier to participation in cardiac rehabilitation programmes is the distance to the centre and transport difficulties (31, 310). A remote CR programme would address this problem, enabling patients to participate in CR from their homes. In our study, participants felt that PA monitoring and prescriptions motivated them to do more and be more physically active.

The study had several limitations. We initially intended to recruit 70 patients. However, due to staffing constraints and accelerometer availability, we could only recruit 51 patients. Even though the sample size of 70 was not based on a sample size calculation, if we had recruited more patients, it may have revealed further patterns in the data. The study was also conducted in a single centre in the UK, which may not represent the wider CR patient population. Furthermore, the study follow-up period was only 8 weeks. A longer follow-up period may have provided further insight into the longer-term effects of the intervention.

## 6.5 Conclusion

It is feasible to conduct a large-scale RCT to assess the effectiveness of an AI-powered remote CR programme compared to a traditional hospital-based programme. The participants found the AI-powered mobile app to be very usable. Our study shows promise in the intervention, which is to successfully increase the baseline fitness level of participants and improve their health-related quality of life. Further research is needed to assess the effectiveness of the remote CR programme.

# CHAPTER 7

# 7. Exploring Patient Experiences in the RECAP Trial: A Qualitative Evaluation

## Key Learning Points from this Chapter

- The qualitative data demonstrated that the delivery of the trial was strongly feasible, reflecting the findings from the quantitative study. They identified several areas that could be improved in the intervention.

- Participants motivation to take part in the study included their desire to help themselves as well as others.

- Barriers to participation in hospital-based sessions included distance from the hospital, travel costs, parking difficulties and work commitments. Several participants preferred a home-based programme for these reasons.

- The participants received the technology well, with room for improvement, including accelerometer synchronisation times.

## 7.1 Introduction

Phase II of the RECAP trial aimed to assess the feasibility of conducting a larger randomised controlled trial (RCT) to determine the effectiveness of an automated home-based CR programme facilitated by artificial intelligence. Quantitative results demonstrated that the delivery of the trial was feasible as assessed by the rates of patient recruitment, randomisation, retention and adherence. Based on the system usability scale assessment, the mobile application was also presented as usable.

Qualitative studies help capture data not recorded in quantitative assessments (318, 319). They can help researchers assess enabling factors and barriers to participation, factors contributing to retention, acceptance of an intervention and implementational challenges. Previous studies have found that common barriers to participation in CR include lack of transport and taking time off work (320). A qualitative study of reasons for dropout from CR programmes in women suggested that offering participants financial assistance for transport may increase participation (321). Exploring patient experiences can inform future trial designs and improve study methodology (322).

Findings from phase I (discussed in Chapter 5), a single-arm study that included interviews with 15 participants, informed the refinement of the RECAP mobile app, which was then tested for the first time in a pilot feasibility RCT. Phase I identified several areas of the technology that needed improvement, which impacted participants' experience and usability of the mobile app. Additional insight from this qualitative study will enable us to make any further adjustments necessary to the intervention before using it in a definitive RCT.

This study (phase II) primarily aimed to explore the experiences of patients enrolled on the RECAP trial to guide improvements to the delivery and design of a future larger trial to assess the intervention's effectiveness. As a secondary aim, participants' intervention experience was explored further following the changes made to the technology after phase I.

## 7.2 Methods

### 7.2.1 Study design

This qualitative study, which involved semi-structured interviews, was nested in a feasibility randomised controlled trial. This study complied with the consolidated criteria for reporting qualitative research (COREQ), a 32-item checklist for interviews and focus groups (323). Informed consent was obtained before participation. The qualitative study design and analysis were guided by the normalisation process theory (NPT), a theoretical framework that explains how complex interventions and processes become integrated into healthcare systems (298).

### 7.2.2 Participants

All participants from both the standard care arm and intervention arm who took part in the RCT were approached for recruitment into the qualitative study. Consecutive sampling was used, and participants were contacted during their final visit to the main RCT or via the phone. Inclusion and exclusion criteria are described in (chapter 6). Semi-structured interviews were employed until data saturation was reached to achieve our study aims (302, 303).

### 7.2.3 Topic guides

Topic guides (Appendix G and Appendix H) were developed with input from a clinical research fellow and surgeon in training (lead author), professor of cardiothoracic surgery, academic cardiovascular unit team staff specialising in trial delivery, cardiac rehabilitation specialist physiotherapists and nurses.

*Table 7.1 Normalisation process theory concepts and mapping them to topic guide questions and final themes. Adapted from Harrison et al. (2023) (324)*

| NPT concepts | Example questions from the topic guide | Pre-determined themes (examples) | Final themes |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Coherence | How familiar were you with the concept of home rehabilitation? | Understanding of home-based vs. hospital-based CR | Trial Uptake: What Motivated Participants to Take Part? |
| | | | - Understanding and Altruism |
| | | | - Personal Benefit |
| Cognitive participation | What motivated you to take part in the programme? | Motivation to participate in trial | What Deterred Them? |
| | | | - Distance and Travel Concerns |
| | | | - Lack of Confidence Post-Heart Attack |
| Collective action | What was your experience with the programme? | Usability of technology and functionality | What Contributed to Retention? |
| | | | - Monitoring |
| | | | - Support from Healthcare Staff |
| Reflexive monitoring | How would you describe your overall experience with the study? | Experience of the programme as a whole | Willingness to Be Randomised and Feelings When Randomised |
| | | | - Acceptance of Randomization |
| | | | - Preferences Despite Acceptance |
| | | What did you think could be done differently or improved? | Fidelity and Receipt of the Trial |
| | | | - Technology Challenges |
| | | | - Successful Implementation to Many |

The interviews were conducted by three male researchers trained in qualitative research, two medical doctors and one surgeon in training. Interviews took place during the final in-person visit at the James Cook University Hospital or over the phone. Participants were given the option to choose what they preferred. The interviewers did not have any prior relationship with the participants. Participants were aware of the job role of the interviewers and about their role in the study. Participants' family members were present during some of the

interviews conducted at the hospital but did not contribute. Notes were taken during the interviews to clarify any aspects of the conversation. They were recorded and transcribed verbatim. It wasn't necessary to repeat any of the interviews or return to any of the transcripts for further comments, as no queries were raised regarding the interview content by any of the researchers.

Qualitative data management and analysis were conducted using the QSR NVivo (Version 12; QSR International, Doncaster, Australia) software. Thematic analysis was used to analyse the data. A hybrid approach to thematic analysis was employed as initial themes were generated deductively, and additional themes were identified inductively during analysis. The analysis was guided by Braun and Clarke's six-phase framework (300). This included familiarisation with the data generating initial codes. Researchers (PW, AG, JT and SH) decided on an initial set of codes used in the analysis informed by the researcher's previous clinical experience and research and the normalisation process theory (NPT), searching for themes, reviewing the themes, defining and naming themes and producing the report. Table 1 demonstrates how the NPT concepts were mapped to topic guide questions and the final themes. The initial codes were decided at the first meeting among the qualitative study group, which included a clinical research fellow (primary author), two medical doctors and a professor in respiratory rehabilitation who supervised the qualitative study. Two coders (AG and JT), medical doctors trained in qualitative research, coded the same two transcripts: one from the standard care arm and another from the intervention arm. The primary author (PW) also coded these transcripts. The qualitative study group (PW, AG, JT and SH) met again to discuss the emerging codes. The codebook was finalised at the meeting, and the remaining transcripts were coded using this codebook. The final themes were developed at the final qualitative study group meeting. Themes were generated using an iterative process. Participants did not provide feedback on the study findings as their views may change over time, and their initial responses may be more accurate (325).

### 7.2.4 Ethics

RECAP trial received NHS research ethics approval from the Berkshire research ethics committee in September 2022 (IRAS 315483). The RCT was registered on the ISRCTN trial database: ISRCTN97352737.

## 7.3 Results

23 semi-structured interviews were conducted, with 12 participants from the intervention arm and 11 from the standard care arm (Figure 1). The interviews lasted between 20 minutes and 60 minutes. Data was initially analysed for each group separately and merged before deriving the themes. Participant characteristics are illustrated in Table 2. None of the participants dropped out of the study.

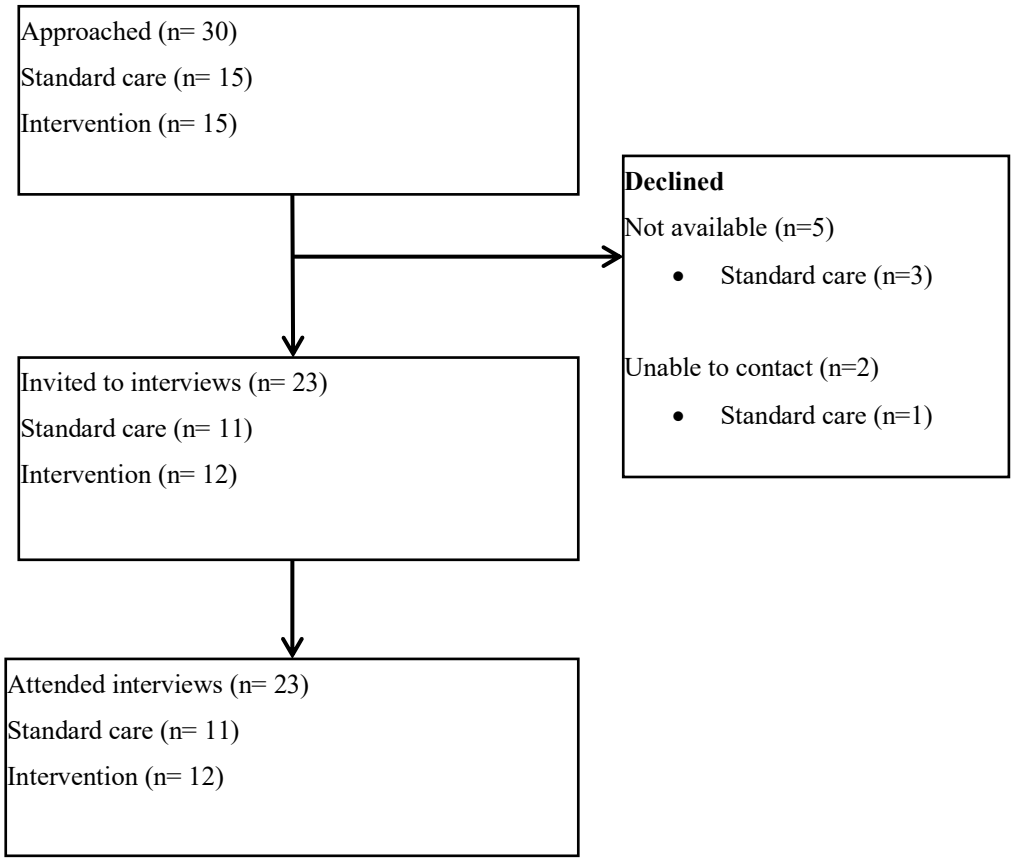



*Figure 7.1 Participant recruitment flow diagram*

*Table 7.2 Baseline characteristics of participants who took part in the qualitative study*

| Characteristic | Intervention (n = 12) | Standard Care (n = 11) | Total (N = 23) |
|---|---|---|---|
| Age, years | | | |
| Mean ± SD | 64.8 ± 7.8 | 61.6 ± 10.6 | 63.3 ± 9.1 |
| Range | 52 - 78 | 38 - 75 | 38 - 78 |
| Female, n (%) | 3 (25.0%) | 3 (27.3%) | 6 (26.1%) |
| Education level, n (%) | | | |
| Higher education | 11 (91.7%) | 9 (81.8%) | 20 (87.0%) |
| Intermediate education | 1 (8.3%) | 2 (18.2%) | 3 (13.0%) |
| Lower education | 0 (0.0%) | 0 (0.0%) | 0 (0.0%) |
| Employed, n (%) | 8 (66.7%) | 6 (54.5%) | 14 (60.9%) |
| With a partner, n (%) | 10 (83.3%) | 11 (100.0%) | 21 (91.3%) |
| Primary treatment, n (%) | | | |
| Medical management | 1 (8.3%) | 4 (36.4%) | 5 (21.7%) |
| PCI | 6 (50.0%) | 4 (36.4%) | 10 (43.5%) |
| CABG | 5 (41.7%) | 3 (27.3%) | 8 (34.8%) |
| 6-Minute Walk Test, meters | | | |
| Mean ± SD | 445.6 ± 93.2 (n=9) 9) | 417.0 ± 85.7 (n=10) | 432.6 ± 88.7 (n=19) |

Five main themes were identified following the analysis. Trial uptake and factors that motivated participants to participate; factors that deterred them; those that contributed to retention; willingness to be randomised and feelings when randomised; and fidelity and receipt of the trial. Figure 2 illustrates the coding tree diagram.

### 7.3.1 Trial Uptake: What Motivated Participants to Take Part?

**Understanding and Altruism**

Participants expressed strong altruistic motivations for taking part in the study. They also saw it as an opportunity to help others while helping themselves. *"Helping myself and other people in the future." "Well, anything that can help medical science to improve has got to be good, hasn't it so?".* Participants were grateful for the care they received as patients and motivated to help the hospital and others. *"I didn't have any problems about it. The hospital asked me, and it's to help other people. As I just said, there's no reason not to agree, is there?".* Another participant felt the hospital saved their life and was very excited at the prospect of being able to give back to the department. *"I might as well give whatever I can back after saving my life".*

One individual also felt thankful for the opportunity to take part in research and to be able to contribute in any way they can. "*Big thanks to the NHS for giving us the opportunity to be part of the project*".

Another participant had a background in chemical research, was aware of the concepts in research and was eager to take part in it himself. He believed it could improve the services offered by the CR team. *"And I think the more we know about things and the more we understand about things, the better service that one will get as a result of that."*

Most participants believed the programme might help them while also helping the hospital with the research project. *"Well, I might get something out of it, and so might the training hospital."* He further stated that research could help future generations and allow them to learn from the experience. *"To help future people come across the same type of thing. To learn by it."*

**Personal Benefit**

Individuals were also motivated by the perceived personal benefits it may offer them. One participant felt it was vital for him to do something different to be more physically active and improve his well-being. *"If we all kind of took the attitude or would not be bothered, then we'd never get any progress."*

Another participant believed the intervention and CR may help them with longer-term prognosis. *"Just for me so I live longer."*

Some participants' families encouraged them to participate in CR and the trial. "I think I think for me it was social, my family motivated me to make those changes."

### 7.3.2 What Deterred Them?

**Distance and Travel Concerns**

As an RCT, participants were aware they may be randomised to either standard care in which exercise classes were based at the hospital or the home-based intervention. Few participants favoured the home-based programme and would have chosen it if they had the choice over the hospital-based programme. Some stated they initially hesitated to sign up for the trial as they would have to travel to the hospital if randomised to standard care. *"Yeah, so. So obviously few it's 1/2-hour drive there 1/2-hour drive back. So, it was about a 32-mile round trip, and the car parking was pretty expensive down at the forum."* In addition to the inconvenience associated with travel, many participants found parking difficult due to the venue not having enough parking spaces or not wanting to pay the parking fee. *"It was a nightmare parking at James Cook. Just in case you're still just never anywhere to park."*

Participants who lived further away from the hospital found the travel particularly difficult. "So, I think that kind of added to the stress levels a bit and then you would hit traffic because I live in a rural area. I'll go down the back roads and get stuck behind tractors and things." In some cases, one-way travel times were over one hour.

**Lack of Confidence Post-Heart Attack**

Some participants felt they had been deconditioned since their discharge from the hospital and needed their confidence building up or extra support to get back to normal. *"But I've lost confidence in that. When I came out, I wasn't sure how far to walk. How often and how fast I should be walking. And so, I was very wary about doing anything really, for fear of doing it again".* Some participants felt they would benefit from the support they would receive in an exercise classroom setting.

Some individuals were also concerned about the possibility of having another myocardial infarction or being unwell for any other reason. *"Will I get something else? I have no idea how fast, how often, how far I should be going, and what I should be doing for fear of happen again."*

Even at times they were exercising well, the fear of having another event deterred them from exercising, "When I was exercising, and I was something I was enjoying. And that played on my mind straight away. That's gonna happen. That could happen again." These participants preferred the traditional hospital-based classes if given the option to choose but decided to sign up for the trial. Most of these participants wanted to help others, and, in some cases, participants lived closer to the hospital, had easy access to transport, or had a partner who supported them.

Other participants preferred the hospital programme as they felt exercising under the supervision of a physiotherapist was safer than exercising at home. One participant felt that attending a hospital-based CR programme may not always be practical due to hospital waiting times and finding a date/time that works for them. *"Well, I would have preferred to like continue like to go to the hospital. You know what I mean? And then they keep an eye on you and see if anything's wrong, can't they? I prefer that, but in these in this day and age, it doesn't always happen like that."*

### 7.3.3 What Contributed to Retention?

**Monitoring**

Most participants found the monitoring aspect of the intervention reassuring. It gave them a sense of comfort knowing that a healthcare professional could view their PA levels regularly. They also knew that the CR department would contact them if there were any concerns about their progress within the programme. *"Well, I think I think I sort of feel almost safe because I thought that the hospital watch is monitoring me 24/7, and you know, if there was anything horrendous happening within my body the hospital would get in touch with me or whatever."*

This was also one of the main reasons some participants were motivated to participate in the study, and it motivated them to continue with the programme. *"Yeah, I felt like I was being monitored by the watch to keep me safe and healthy, "sense of safety, I was being monitored."*

Some individuals felt the intervention offered a means to be more regularly monitored than the standard care arm as the accelerometers captured their PA data in real-time and the data were sent to the hospital. "*Whereas with the watch it's monitoring year 24/7. So, you feel like, oh, big brother watching me, I better do something."* Another participant stated, *"And I think it was more beneficial to do this programme than it was to just physically going to the hospital and get those basic checks, and they were they were just one after maybe a few. With this on a daily basis, I could see exactly what was going on".*

**Support from Healthcare Staff**

Most participants also appreciated the help and support they received from the healthcare staff. The standard care arm participants had direct contact with a physiotherapist and/or a nurse during the exercise classes. Those randomised to the intervention arm were also given a contact number to call the department if they had any questions or concerns. *"Well, I've I found all the recovery for physiotherapy, everything every professional that I've been associated with, have been really, really good to me. They've explained things for me from start to finish. They've helped me that they're always concerned about how I'm feeling, what I'm doing. I've found it very positive experience."*

Some individuals in the intervention arms found the CR sessions educational. They received information about their operation as well as the recovery. They found the explanations

helpful and motivated them to be more physically active. *"Everyone should got those little worries about having a major operation. Is it the right thing to do and honour doing this OK by doing it right when you've got these professionals encouraging you, explaining stuff to you, it's very helpful, and it does motivate you."*

Some standard care arm participants also appreciated the educational lectures' classroom aspect. It allowed them to ask questions and also learn from the questions asked by their peers. *"The team, Jesus Christ, are out of this world; they were just so relaxing, and the information was filled with. I couldn't believe it, you have anything to ask any questions, it wasn't just me. Obviously, other people ask questions then you get the answer."*

**Motivational Quotes**

The mobile app displayed a new motivational quote every time a participant opened the home screen. These quotes were generally received with mixed feedback. When asked if the quotes helped them with motivation, one participant stated, *"It is actually a Winston Churchill quote. So yeah, I tried those. Yeah, I did.".* Another participant didn't express any strong feelings about them. *"I did notice them. They were OK".*

One individual felt the quotes didn't help them with motivation. "Yeah, yeah. Yeah. Well, I don't know. I don't think it helps. I used to enjoy reading them, but I don't. I wouldn't say it helps."

### 7.3.4 Willingness to Be Randomised and Feelings When Randomised

**Acceptance of Randomization**

Most participants did not prefer which arm they were randomly assigned. *"Erm, I was just, I was just erm, I was happy to do either one, to be honest."* They trusted the healthcare team would do what was best for them and were happy to accept the randomisation they received. *"Whatever you say I'll do, I was quite happy."*

Among the participants, some were very skilled with technology, whilst others didn't have much experience even using the basic features of a phone. *"I'm great. I'm OK with technology. I was. I used to be a software engineer. So, software engineering, sort of technologies familiar but I didn't mind either way." "You know, I'm a dinosaur, so. Life moves on rapidly now. Technology moves on rapidly, and it's over my head. Truthfully."* Being able to contact the CR department with any queries about rehabilitation or the technology reassured them that help was available if they needed it. *"I think I was totally happy to be independent because I knew that I had that phone number to call If I had any concerns."*

**Preferences Despite Acceptance**

Most participants who had a preference tend to prefer the home-based programme to the hospital programme. This was primarily due to convenience and not travelling to the hospital weekly. *"I was I was pleased to do a home programme. Yeah, because it's very inconvenient having to get into a car and come down to the hospital, try and find a a parking space. And come to the hospital."* Some participants felt they couldn't drive due to DVLA restrictions. This meant they had to rely on their family or friends to drive them to the hospital. *"You're not able to drive for months. After a heart attack. DVLA won't allow you to, so I would have had to have had somebody to take me. Which would have been a little bit inconvenient.".*

Fear or infection was also stated as a reason one participant preferred the home-based programme. "I was also quite concerned with the nature of the room. It was sort of, I am a vulnerable person in terms of COVID, not just because of the heart problem but other comorbidities."

### 7.3.5 Fidelity and Receipt of the Trial

**Technology Challenges**

Several participants highlighted issues they experienced with the accelerometers due to delays in synchronisation times. Following the learnings from Phase I, we have informed participants about this issue, and they were advised to manually synchronise their

accelerometers daily. However, despite this, it continued to be a problem and adversely affected participants' experience. *"The thing with the watch, it didn't tell you till the next day how far you've progressed that day."* The synchronisation delay also meant participants couldn't monitor their progress in real-time. *"So, if you don't, if you don't 5800 steps, it will push you to 6000 if you knew, but you didn't know till the next day how many you'd done."*

**Successful Implementation for Many**

Despite the challenges with synchronisation, many participants enjoyed the programme and didn't experience any issues. *"The watch, or the app. It was very easy, very easy to use and very accessible like I thought there's [no] barriers to that".* This resulted in participants having a very positive experience with the programme. *"Yeah. No, it works seamlessly. There's no bother with it at all."* Even those with less technical expertise found the programme user-friendly. *"No, I think it was just really straightforward". "It was quite a good model as well. It was, you know, it was robust."*

Individuals reported that having goals motivated them to engage in more physical activity weekly. It gave them something to work towards. *"When you're doing. These exercises, and so I thought, oh right, I've got 9000 steps to walk today. That's great. I'll, I'll, I'll. I'll achieve that, you know? And so, I knew, I knew my goals, and I and I stuck to them. That gave me confidence straight away that I was being told by somebody."*

Participants understood that goals would be prescribed by artificial intelligence (AI), but they would be regularly assessed to ensure they were appropriate for each participant. One individual stated AI could still motivate them. *"I think I think that kind of a Bit of reinforcement. For when you when you had a good day, and you've done well. Everyone likes the pat on the back, an artificial intelligence part on the back is just as well accepted, I think, by most of us."* However, another participant stated they did not believe in AI and appreciated the constant input they got from a clinician. *"I would want to have somebody have to look at it, you know, a human being. Yeah, they're up. But that's because I'm old, and I don't have any faith in AI."*

**Exercise Appropriateness and Progression**

The physical activity goals prescribed by the algorithm included step count goals and moderate to vigorous physical activity (MVPA) goals. These domains were explained to the participants at the initial visit prior to the commencement of the home-based programme. However, there was one individual who didn't understand the concept of MVPA. *"Yeah, I mean, I understood the steps. Uh. And I didn't; there was a sort of there was like a sleep time quiet time. There was a, I think, a vigorous exercise."*

Some participants were already very active and were used to monitoring their PA levels. These individuals were used to working towards PA goals and found the programme relatively straightforward. *"It was relatively easy for me. The steps of and one thing another because I was already walking about, well, a minimum of 2 1/2 miles a day, which is about what? 6000 steps."*

They appreciated that the machine learning algorithm aimed to increase their PA levels over time safely. They also had access to exercise videos via the mobile app. The difficulty of these exercises increased every two weeks. *"The sort of increase in the intensity and the distance, I suppose it would be ultimately, but yeah, the intensity, especially in the little video things that were you could sort of increase the levels so."*

The convenience of the home-based programme also meant participants found it practical to follow through the exercises in the videos whilst also achieving the weekly PA goals. *"It's achievable, definitely. Yeah, it's easier to do at home than having to go out. It's if you're working. I was working. So, it's suits me well."*

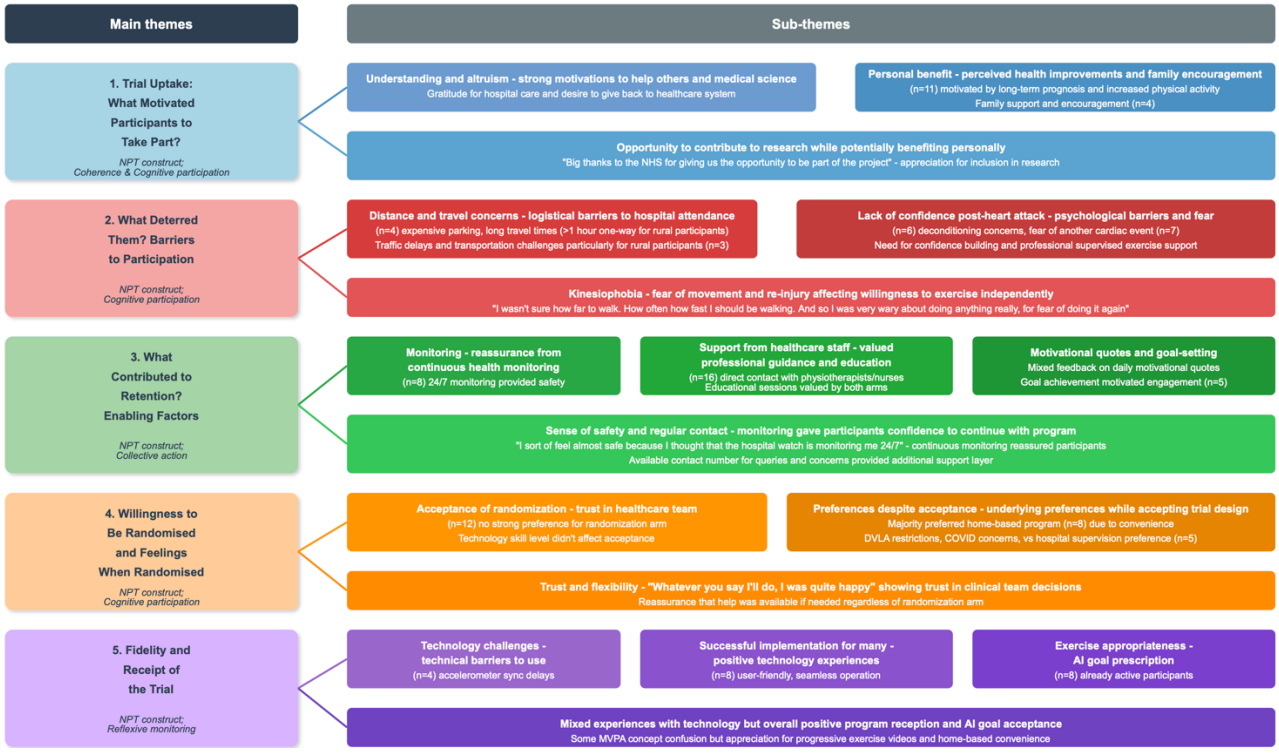



*Figure 7.2 Coding tree demonstrating the main themes and the sub-themes*

## 7.4 Discussion

This study aimed to explore participants' experience with the RECAP trial and the intervention, identify enabling factors and barriers to participation, determine the feasibility of the delivery, and improve the design of a future definitive trial. It reflected the findings from the quantitative results that the delivery of the RECAP trial was feasible. This study used NPT as a theoretical framework to examine how participants normalised the AI-enabled home-based CR intervention across the four key implementation domains.

This study demonstrated that participants' strong altruistic motivation contributed to their participation. They were also driven by their desire to improve their own PA levels and longer-term prognosis, encouraged by their family members. In keeping with previously published studies, significant barriers to participation in the RECAP trial included distance from the hospital, inconvenience associated with travel and parking, having to take time off from work, and CR session schedules not aligning with their timetable (326, 327). Most of

these participants preferred the home-based programme if given the option. The reasons identified here were also the primary reasons for participants declining to participate in the RECAP trial.

A common barrier to participation in the home-based programme was participants' preference to be supervised by a healthcare professional during exercise. Several individuals felt their confidence levels had decreased following their discharge from the hospital. They were also fearful of having further cardiac events. Previous studies have identified fear of movement (kinesiophobia) as a barrier to participation in CR (328, 329). One study found that kinesiophobia was associated with a patient's cardiac anxiety levels, social status and educational level (328). These fears were also reflected in our qualitative study.

Some participants valued the regular monitoring aspect of the home-based programme more than the once weekly supervised exercise classes offered by the hospital programme. Monitoring and feedback are important aspects of a home-based CR programme and can allow healthcare professionals to regularly update participants' performance (330). A literature review of virtual healthcare solutions for CR concluded that digital health interventions can potentially increase user engagement and adherence (331). This was particularly true when an intervention employed several features, including PA monitoring and personalised goal setting (331). However, none of the studies in this review employed AI to personalise PA goal prescriptions.

Participants also found the mobile app and intervention usable and acceptable. This was reflected in the quantitative assessments conducted during the RECAP trial, which included the system usability scale and mobile app usability questionnaire.

This study had several strengths. We included participants with diverse characteristics from both arms. We also reached information power to achieve our study aims after conducting 23 interviews (332). Furthermore, we followed a robust methodology, adhering to the COREQ guidelines and thematic analysis framework.

This study had several limitations. This study's participants had a high level of education, and the study was conducted in a single centre. Therefore, the findings may not apply to different

healthcare systems or populations. Furthermore, several participants experienced issues with the accelerometer synchronisation times, which may have impacted their experience with the intervention, including adherence.

This study highlighted several areas that will need addressing in future studies, including the difficulties participants face with accelerometer synchronisation times. One possible solution is employing a different brand of accelerometers with an automatic synchronisation feature or adapting the mobile app to connect to the participant's smartwatch. Another essential improvement would involve educating the participants more on MVPA minutes before the start of the intervention. This may be done by providing further details in the participant handbook and explaining the concept of MVPA during the initial visit. Participants also highlighted the need for more education in addition to the PA component of CR. This may be implemented by including more educational videos accessible via the mobile app. In this study, participants' motivation to take part in the trial was also explored. However, it is essential to note that as participants who declined to participate were not included in this analysis, their views were not considered. In this study, we also did not perform member checking, which, despite its limitations, may have given us further information that was not initially captured in the interviews.

Based on our findings, we recommend that further large-scale studies be conducted to establish the effectiveness of an AI-enabled home-based CR programme.

## 7.5 Conclusion

This qualitative study demonstrated that the delivery of the RECAP trial was strongly feasible. A home-based AI-facilitated CR programme is acceptable to a patient population with diverse characteristics and technical skill levels. Refinements to the intervention may further enhance the mobile app's usability and the intervention's acceptability.

# CHAPTER 8

# 8. General Discussion and Conclusion

## Key Learning Points from this Chapter

- The RECAP feasibility RCT exceeded all pre-defined feasibility criteria, demonstrating it is feasible to conduct an RCT to assess the effectiveness of a home-based CR programme facilitated by a mobile app powered by AI. There were no adverse safety events recorded.

- The mobile application achieved excellent usability and acceptability, and the ML algorithm could prescribe PA goals that did not require manual adjustment.

- An automated home-based CR programme addresses key barriers to traditional CR, potentially improving access and reducing waiting times for traditional CR programmes.

General Discussion and Conclusion

- This represents the first NHS-based feasibility study of an AI-enabled PA goal prescription in CR, providing a framework for future digital health interventions.

# Thesis Overview

This thesis describes an evidence-based approach for developing and evaluating a mobile application, a web portal and a machine learning algorithm. This intervention was then tested in a mixed-methods single-arm usability study. Following this, we conducted a mixed-methods feasibility RCT to assess the feasibility of conducting a larger-scale definitive RCT to evaluate the effectiveness of this intervention.

## 8.1 Principal Findings

### 8.1.1 Feasibility of Conducting a Definitive RCT to Assess the Effectiveness of an AI-Powered/Automated Digital Cardiac Rehabilitation Programme

The results from this study demonstrated that it is feasible to conduct a larger-scale definitive RCT to assess the effectiveness of a home-based AI-powered cardiac rehabilitation programme. The study exceeded patient recruitment, randomisation, dropout, and adherence targets. Targets of ≥ 70%, ≥ 80%, ≤ 20%, and≥ 75% were set for each domain, respectively. In this RCT, the respective targets achieved were 85%, 100%, 86% and 92%, respectively (Table 8.1). The qualitative study also reflected these findings as it concluded that it is strongly feasible to conduct a definitive RCT.

*Table 8.1 Progression Criteria for a Definitive RCT*

| | Go – proceed with RCT | Amend – proceed with changes | Stop – do not proceed unless changes are possible | Outcomes achieved in this RCT |
|---|---|---|---|---|
| 1. Feasibility of patient recruitment | ≥ 70% of approached patients consented | 50 – 70% of approached patients consented | ≤ 50% of approached patients consented | 85% |

| | | | | |
|---|---|---|---|---|
| 2. Feasibility of patient randomisation | ≥ 80% of the patients eligible and consented randomised | 50 – 80% of the patients eligible and consented randomised | ≤ 50% of patients eligible and consented randomised | 100% |
| 3.Feasibility of patient retention (at 8 weeks following randomisation) | ≤ 20% of patients dropped out after randomisation | 20 – 50% of patients dropped out after randomisation | ≥ 50% of patients dropped out after randomisation | *86%* |
| 4. Adherence to intervention | ≥ 75% of patients using the app weekly | ≥ 50% of patients using the app weekly | ≤ 50% of patients using the app weekly | 92% |
| 5.Delivery of trial | Delivery of trial judged to be strongly feasible by qualitative data | Delivery of trial judged to be feasible by qualitative data | Delivery of trial judged to be possibly feasible by qualitative data | Qualitative data indicated the delivery of the trial is highly feasible |

Across both phase I and phase II of this study results established high mobile app usability scores despite the varying technological capabilities of participants. Qualitative testing following both phases allowed us to identify areas that needed improvement and were subsequently addressed.

### 8.1.2 Performance of Machine Learning Models

We developed and evaluated several ML models for prescribing weekly step count goals. Models including linear regression, random forest, k-nearest neighbour and XGBoost were tested. XGBoost was found to have a high-performance score similar to the other models. However, due to the limitations of our initial model development approach, these results were invalid. The high-performance scores were likely due to an error in the training process leading to target leakage. This will be discussed in more detail in the limitations section of this chapter. The current week's step count and MVPA minutes completed were the strongest predictors of the following week's step count and MVPA minutes.

As an ML model was employed to prescribe PA goals, a HCP constantly reviewed the goals prescribed for each participant every week to ensure they were appropriate and safe. The web portal also offered HCPs the option to amend and override the goals at any point manually if they deemed it necessary. We also recorded the number of times this was performed in both phases of this study. However, a manual amendment wasn't indicated or enacted at any point for any participant, as all the prescribed goals were considered appropriate and safe.

No adverse events related to the intervention or ML-based PA goal prescriptions were reported.

### 8.1.3 User Experience and Acceptance of the Intervention

The mobile app was evaluated in both an alpha and beta testing phase. Following the feasibility RCT, participants rated the mobile app highly usable, receiving a score of 82.5 on the SUS. These results were reflected in the MAUQ scores, where participants scored 6/7 for app ease of use. The SUS score slightly improved since phase I, where the mean score was 82. On the other hand, the MAUQ score was higher (6.5/7) for ease of use following phase I. Qualitative interviews reiterated the findings from these usability questionnaires, as even participants with little prior technical skills could use the app without extensive training.

The qualitative interviews following phase I, which included staff focus groups, revealed that HCPs were averse to AI prescribing PA goals for patients. This was due to the fear of AI replacing their jobs and not having previous experience with digital health interventions facilitating a home-based programme. However, despite these reservations, the CR team acknowledged the potential benefits of an automated CR programme. They felt it might be particularly beneficial if a hybrid programme, consisting of hospital-based classes and home-based exercises, could be offered to patients.

## 8.2 Clinical Implications of an Automated Home-based CR Programme

### 8.2.1 Addressing Low CR Participation Rates

Participation in traditional CR programmes remains low despite the numerous benefits (333). Some key barriers to participation include transportation difficulties, work commitments, geographical constraints and fear of infection (334-336). Fear of infection was particularly concerning during and after the COVID-19 pandemic (337). A qualitative study of phase II identified the same factors as barriers to participation in the RCT and CR.

An AI-powered home-based programme would address these barriers, allowing patients to undergo rehabilitation independently while working around personal and work commitments. They will also be at reduced risk of infection. However, further work is necessary to build an effective and validated ML model capable of prescribing PA goals. Our study findings are insufficient to determine the effectiveness of an AI-powered PA goal prescription model.

### 8.2.2 Personalised Medicine Implementation

Prescribing personalised exercises for CR patients can be challenging as many factors, including a patient's medication and current comorbidities, must be considered (338). One of the current personalised approaches used in the UK for determining target heart rates during exercise is based on predicting the maximal heart rate (338). The same approach is used for patients who are on beta-blockers. However, this method may not be practical for these patients, as beta-blockers suppress heart rate response during exercise, making traditional heart rate targets unreliable (338).

Our ML model took into account a patient's baseline characteristics, comorbidities, medications, and week's PA levels. AI can prescribe personalised exercises for patients based on their phenotype and progress in an exercise programme. Furthermore, an AI-powered programme could negate the need for human input if successfully implemented and its safety is established. This would allow CR centres to enrol more patients simultaneously.

### 8.2.3 Alternative Approaches for CR

The current model for CR may be amended to combine both aspects of hospital-based classes and an AI-powered home-based CR programme based on a patient's preference. Traditional CR programmes do not entail participant monitoring at home. However, if remote monitoring was offered as part of a standard CR programme, participants may be more likely to maintain their PA levels throughout the week. This was reflected in the qualitative component of the study as participants stated they were more likely to exercise when being monitored.

Furthermore, live monitoring of a patient's heart rate and oxygen saturation during traditional supervised exercise classes allows HCPs to amend exercise prescriptions accordingly.

## 8.3 Methodological and Technical Contributions

### 8.3.1 Software Development Approach

To the best of our knowledge, this was the first CR mobile app and web portal to be developed by a clinician. We followed an evidence-based approach in the development of this app. Iterative development with user feedback allowed us to refine it with each iteration, including testing the app in alpha, beta and clinical testing phases.

The design and development of the app and web portal also involved multi-stakeholders, including patients, clinicians and software developers.

### 8.3.2 Machine Learning in Healthcare

Following the development of the ML model, it was deployed to an online server via a custom-made API. This study also demonstrated the feasibility of retrieving an ML model's output (PA goal prescriptions) via a custom-made API in real time.

We also demonstrated the technical infrastructure for utilising PA data gathered in real-time via accelerometers as input parameters in an ML model and retrieving it via a mobile app. However, our ML model's clinical validity was compromised by methodological limitations.

Furthermore, we assessed this intervention's acceptability to patients and staff in a clinical trial, demonstrating its usability and acceptability. The intervention was well received by the CR team, as well as the patients. Participants rated the mobile app as highly usable, and the intervention was delivered as per the study protocol. Qualitative study demonstrated that both the staff and patients felt that an automated mobile app facilitated home-based CR programme is an acceptable alternative to traditional CR.

### 8.3.3 Mixed-Methods Evaluation

During all stages of this intervention's development and evaluation, a mixed-methods approach was employed, consisting of quantitative and qualitative methods. This methodological triangulation strengthens the validity of findings by capturing both measurable outcomes and experiential insights, addressing a common limitation in digital health interventions where quantitative metrics alone may miss important user experience factors (339). Multiple stakeholders' perspectives, including clinicians, patients and software developers, were taken on board. This study received regular input from the academic cardiovascular unit team of the South Tees University Hospital, Middlesbrough, including a professor of cardiothoracic surgery and clinical trials managers. Such embedded clinical oversight ensured that the intervention remained grounded in real-world practice while maintaining scientific rigor, potentially enhancing both the intervention's clinical relevance and its likelihood of successful implementation.

A comprehensive usability assessment was conducted using the SUS and MAUQ questionnaires following each iteration of the mobile app. The 6MWT distance was employed to evaluate the effect of the intervention on physical fitness, while questionnaires were used to assess the impact on quality of life.

## 8.4 Challenges and Limitations

### 8.4.1 Technical Challenges

## Machine Learning Algorithm Limitations

Our approach to the development of the initial ML model had several limitations. The first version of the model was used to prescribe PA goals in Phase I of the RECAP Trial. Finding the ideal dataset to train a model in healthcare remains challenging due to concerns about data availability, privacy and consent. We had access to the data from the OPTICARE trial assessing outcomes after CR. However, this dataset lacked weekly PA measurements as these measures were taken at only 3 months, 12 months and 18 months. It failed to capture the progression of PA trends over the weeks. As a result, a new variable was created based on the increase in PA levels from baseline to 3 months. The difference was evenly divided by the number of weeks and added to the baseline value. This assumed a linear increase in PA levels, not considering the recovery timeline. A better approach would have been to calculate a change score, which may still not consider the variation of the PA levels over time. The ideal dataset will contain PA-level data measured daily.

Target leakage occurs when information about the target variable (the independent variable that the ML model aims to predict) leaks into the input features being used to predict the target. This gives the model an unfair advantage as it can access the target variable or its properties. Data leakage may occur in various forms and stages, including hyper-parameter tuning, data normalisation, and augmentation. When a dataset is not correctly split into training and test data and overlap occurs, it may also lead to data leakage. This could substantially impact a model's performance and defeats the purpose of dividing the data into a train and test split (340). Unfortunately, in the field of ML and even in published literature, data leakage can be identified when evaluating the methodology of some studies (341).

Kapoor et al. systematically investigated the reproducibility of ML models and surveyed literature. They identified 17 fields where data leakage has happened, affecting 294 papers, including those in medicine, resulting in baseless conclusions. The authors recommended that the train and test data be separate without any interactions between them during pre-processing, creation of models, or evaluation (342). In another study of predictive neuroimaging, ten out of the 57 included studies may have leaked data due to performing dimensionality reduction before creating the train/test split. This can drastically affect the results of a study, as well as its reproducibility (343).

In creating our initial ML model, one instance in which data leakage occurred was when missing values were addressed using imputation. Our imputation was done before the dataset was split into training and test data. This meant that the statistical properties of both splits were used to calculate the missing values via our imputation approach, resulting in data leakage. This would have been avoided if the training and test split occurred earlier in the ML model development, as it would have preserved the statistical properties of the two splits without leaking from one to the other. In this approach, once the missing values were calculated for the training split based on the training dataset properties, it would be applied to the test split. Target leakage can also happen in target encoding, where categorical variables are replaced with the mean target value for samples with that category, likely resulting in overfitting (344). Data leakage can be exacerbated in smaller datasets (345). For the initial model development new " perception " feature was created to replicate the BORG scale rating of perceived exertion. In doing so, the percentage increase in the target variable (the goal step count) was taken into account and a number assigned to the perception variable to reflect the percentage increase. This resulted in target leakage as statistical properties of the target, or the independent variable were leaked into the dependent variables. The initial ML model assessment results should be interpreted cautiously given the methodological limitations.

It is important to note that the ML model and the intervention architecture were designed to be trained automatically following the conclusion of phase I of the RECAP trial based on new data that was collected. The latest data that was captured following phase I did not have any issues surrounding target leakage. The model was retrained using data from the Opticare dataset and phase I, before starting phase II. Therefore, the latest model that was used in the feasibility study did not have any target leakage issues.

## Accelerometer Synchronisation Issues

Issues with accelerometer synchronisation times were identified in all three stages of testing. However, despite making amendments to mitigate the impact and inconvenience to the participants, participants continued to experience issues with synchronisation times. Following each stage of intervention testing, changes were made to the intervention, which minimised its impact on participants following each iteration. However, this adversely

impacted participants' experience with the mobile app and the programme. The accelerometers were initially intended to synchronise automatically. However, there were times when participants were required to do it themselves manually.

These issues will need to be addressed prior to conducting a larger scale RCT. Since the software for accelerometers is managed by ActiGraph, other parties will not be able to make changes to this software. Therefore, if ActiGraph accelerometers are to be used in future studies, it is critical to ensure the software will function as intended. Alternatively, other accelerometer devices such as Fitbit or Apple Watches may be used. Prior to using these in research, it is important to ensure their scientific validity (346).

### 8.4.2 Study Limitations

#### Sample Size and Demographics

The study was conducted in a single NHS hospital in the North of England, so the findings may not be generalisable to other populations. Furthermore, in phase II, the feasibility RCT was conducted with a reduced sample size of only 51 participants. We originally intended to recruit 70 patients as a guide to estimate the standard deviation for continuous outcomes based on previously published literature (347). However, we had to conclude the study after recruiting only 51 participants due to time constraints and the availability of accelerometer devices. This impacted the timeline of the study as recruitment was slower than expected. CR clinic cancellations due to staff sickness resulted in the department offering fewer appointments to patients on average. Nevertheless, a feasibility study does not require a formal sample size calculation, and 51 participants were sufficient to achieve our study objectives (348, 349).

It is also worth noting that most participants in both phases of this study were male. This is in keeping with the average CR population where only 25% of the participants tend to be female (350, 351). This may limit the generalisability of our study findings to the female population. Future studies could explore if an automated home-based CR programme could improve CR uptake among patients who may be underrepresented, including those who are female, elderly and less educated.

### Outcome Measurement

Each participant was in the study for eight weeks following their initial visit. A longer follow-up period may have allowed us to evaluate the long-term impact of the intervention on participants including the effect of an automated programme on PA and health-related quality of life measures (352).

## 8.4.3 Implementation Challenges

### Integrating the Programme in NHS Hospitals

Integrating a novel digital healthcare intervention requires certain IT infrastructures to be in place. These may include servers compatible with data protection legislation and hospital computers that allow installation of external software. When a new system is adopted in a hospital, the IT department's cooperation and the hospital information governance's team approval will be required.

RECAP mobile app was developed and used in-house within the same NHS trust. Therefore, it wasn't necessary to obtain MHRA approval. However, if the mobile app is to be used externally, further approval will be necessary (353).

RECAP Trial software was developed and delivered by the author (PW), who was also responsible for the day-to-day administration of the trial, including participant recruitment and conducting trial assessments. As a result, there was no need to train other HCPs to demonstrate to participants how to operate the mobile app and troubleshoot any issues they may experience with it. However, if this programme were to be used as part of a multi-centre study or if it were to be adapted into clinical practice, staff training would be crucial to ensure successful implementation.

### Patient Selection

The results from our study demonstrated that participants with varying technical skills could use the software successfully. However, as these findings may not be generalisable for other populations, some participants who are not digitally literate may not find the technology usable. Therefore, this will need further evaluation in a larger definitive RCT.

Due to device compatibility requirements, participants will need relatively newer smartphones to install the RECAP trial mobile app. This is also the case when successfully installing the Actigraph Accelerometer mobile app, which allowed participants to synchronise their PA data.

These factors should be taken into consideration when a definitive RCT is planned. Updating the mobile app and employing other makes of accelerometers, including Fitbit devices and Apple Watches, may overcome this barrier.

The study was conducted at the James Cook University Hospital in Middlesbrough, where the patient population includes individuals from low socio-economic backgrounds (354). Future studies could explore the impact of educational level and socio-economic status on adherence to the CR programme.

## 8.5 Comparison with Existing Literature

### 8.5.1 Systematic Review Findings Context

A systematic review and market analysis of the current apps in the Apple app store and Google Play store was conducted before the design and development of the intervention. Several behavioural change techniques, including goal setting, physical activity monitoring and motivational messaging, were identified as approaches used by existing mobile apps in CR. Following the findings from this systematic review, we integrated these BCT's into the RECAP trial mobile app.

None of the programmes discussed in the included articles employed AI for PA goal prescription.

### 8.5.2 Novel Contributions

This thesis represents an innovative approach to digital cardiac rehabilitation implementation using an AI-powered PA goal prescription CR intervention in a feasibility RCT in the NHS. While developing the ML algorithm, we evaluated several ML models, including XGBoost, random forest, K-nearest neighbour and linear regression using data from the OPTICARE dataset. Through our clinical trial, we collected additional data with new variables and features, allowing us to train a new ML model. The findings from this study would enable us to develop a more effective ML algorithm capable of prescribing personalised PA goals to patients and further refine our development approach.

We also developed a continuously learning ML model to prescribe the PA goals. It is important to note that this work wasn't intended to evaluate the effectiveness of the ML goals or the intervention. Nevertheless, we aimed to establish the feasibility of implementing a continuously adapting ML model to prescribe PA goals as part of a home-based CR programme.

This work was also unique as it was the first time a CR mobile app and web portal was designed and developed by a hospital clinician rather than external commercial developers. This allowed us to combine clinical expertise and software development skills to develop a novel intervention and regularly update it without relying on any third party. We were also able to establish the mobile app's usability using the system usability scale. The SUS can be used with a small sample size, yielding reliable results (355, 356). Therefore, this study established the mobile app's usability by employing quantitative assessments using questionnaires and app analytical and qualitative data.

In this study, we also demonstrated the real-world feasibility of conducting an RCT to assess the effectiveness of this intervention.

## 8.6 Clinical and Policy Implications

### 8.6.1 Healthcare Service Implications

#### Capacity and Access

This intervention can potentially increase CR participation rates, as it would allow participants to participate in CR from home. This will be particularly beneficial for patients living in remote areas without easy access to hospital-based CR sessions. It can also reduce the burden on hospital-based services as each CR session has a maximum participant limit. This also means that, in some cases, patients have to wait until a space in an exercise class that aligns with their schedule is found. A home-based CR programme would reduce the waiting times. Shorter waiting times for CR may also improve patient outcomes, including exercise capacity (357).

#### Resource Allocation

A fully automated home-based CR programme may also be cost-effective for a healthcare system as associated staffing costs are reduced, eliminating the need for supervised exercise classes. This is also in keeping with the long-term NHS plan of making services more digital (358).

With the development of new technologies and AI, the role of the HCP is also evolving (359, 360). Our qualitative interviews revealed reservations about CR clinical staff digital technologies and the fear of AI replacing their jobs. This has been previously highlighted as a concern in literature (360). However, integrating AI into clinical practice can improve patients while enhancing the job of HCPs.

### 8.6.2 Quality and Safety Considerations

#### Adverse Events

There were no adverse events reported during the study. All of the PA goals prescribed by the algorithm were deemed to be appropriate for the participants. However, definitive larger scale studies are needed to further analyse the safety of the intervention.

## Clinical Governance

NHS England has published guidance to help staff understand, develop and adopt AI (361). The guidance recommends developing AI in collaboration with clinicians, software engineers, data scientists, and product designers. The guidance highlights the importance of evaluation and validation of AI algorithms, including internal validation, external validation, local validation, prospective clinical studies and ongoing monitoring (361).

The development of our ML model involved the collaboration of individuals with expertise in software development, data science, product designing, and clinicians. We have also tested the model in-house using training data and a clinical study. The goals prescribed by the model were also constantly monitored by HCPs. However, further clinical studies are needed to validate the current model whilst making adaptations to address the limitations identified in this study (361).

## Patient Data Handling and Security

In developing this intervention, patient data was handled following GDPR and local and national guidelines (362, 363). During the intervention and clinical trial development, patient data was anonymised before being stored in secure online servers. No personal data were stored on participants' mobile devices. In the event of a data leak or a hack, this will ensure participant data won't be put at risk. Secure Socket Layer (SSL) certificates were employed while developing the web portal to ensure secure data transmission via the internet (364). SSL certificates allow encrypted connections to be established between clients and web servers. In this process, data is converted into a cryptographic format, making it uninterpretable to anyone attempting to intercept the connection (364).

Future studies and adaption into clinical practice will require patient data to be stored on their own mobile devices. Therefore, it is vital to explore secure forms of data storage and handling, including cloud-based solutions, while complying with data protection guidelines (365, 366).

# 8.7 Future Research Directions

## 8.7.1 Effectiveness Studies

### Definitive RCT Design

RECAP Phase II concluded that conducting a larger definitive RCT is feasible to assess the effectiveness of a home-based AI-powered CR programme. We also identified the 6-minute walk test distance physical component score and mental component score of SF36 as potential outcome measures.

A definitive RCT would ideally be multi-centred to capture a population with broader demographics and a bigger sample size based on a power calculation.

RECAP Phase II feasibility RCT stratified participants based on the treatment received (surgical vs. non-surgical). However, due to the small sample size of the study, it was not possible to draw conclusions about the impact of the intervention on each group. Future studies with larger sample sizes may allow researchers to analyse the differential impact of the intervention based on the treatment received.

Before proceeding to a definitive RCT, refinements to the methodology for developing the ML model will be required. This will involve testing different machine learning algorithms using the newly collected patient data and evaluating their performance in generating or optimising exercise prescriptions. Hyperparameter tuning will then be performed to refine the selected model and achieve optimal predictive performance. Performance on the new dataset will be compared with that on the original training data to assess the impact of the new patient population on predictive accuracy. Importantly, this will also enable comparison between predicted exercise prescriptions and the patients' actual achieved outcomes.

### Effectiveness and Cost-analysis

We recommend that future trials also evaluate the effectiveness of a hybrid model of CR and compare that with the effectiveness of a home-based CR programme alone. Participants attending traditional CR sessions may be less likely to exercise outside of the sessions. A hybrid model would enable participants to be monitored at home and receive PA goals. However, this would require a bigger sample size, which may be difficult due to funding limitations. Qualitative data analysis from phase II of the RECAP trial demonstrated that HCPs may prefer to offer patients a hybrid approach.

An automated home-based CR programme would remove the need for an HCP to prescribe exercises, and the costs associated with facilitating supervised exercise classes. However, an automated programme may need to be closely monitored to ensure its safety, particularly during the early stages of implementation. Evaluating the cost-effectiveness of each programme would also allow healthcare organisations and systems to make informed financial decisions whilst providing patients the option of choosing a CR programme that works best for them.

### 8.7.2 Technology Development

#### Algorithm Refinement

The development and refinement of an ML model involves several stages. The quality of training data and the data pipeline are important factors in model development (367). Thorough testing using diverse patient data is important to ensure the model is effective for different patient populations.

A definitive RCT would also allow us to collect more data to train and effectively validate an ML model.

The model employed in the RECAP trial was based on data collected from the OPTICARE trial conducted in the Netherlands. It aimed to predict the participants' goals for next week. This approach had several limitations. Other approaches to the model development include training a model to predict PA goals, taking into account goals prescribed by an HCP.

Including this in the feature set would allow the model to identify any relationships between the HCP-prescribed goals vs actual PA levels achieved. Broadening the approach to ML model development may also allow researchers to develop a risk score and identify participants who are less likely to participate in and complete CR.

Future research should also focus on collecting more health-specific data, including heart rate and oxygen saturation. These metrics may be used to train ML models analysing the effect of these features on PA goal prescriptions.

## Platform Enhancement

Qualitative interviews conducted during the phase II clinical trial demonstrated that participants experienced issues with accelerometer synchronisation times. Some individuals also preferred using their smartwatches to monitor their PA levels. Future research and clinical implementation should address the device synchronisation difficulties that have the potential to impact participant experience, usability, and adherence to intervention, and they should consider offering participants the option to use their own devices.

The mobile app and the intervention could be developed further to include more educational materials, including dietary advice, psychosocial management and vocational support, as the current version primarily focused on PA (368).

The current version of the mobile app allows users to increase the size of the text to make it more readable. The app could be further improved to support multiple languages for non-English speakers and offer accessibility features such as voice-overs for users with reading difficulties. As a large proportion of the user base is expected to consist of older adults, the application has been intentionally designed to be simple and free of unnecessary complexity. Users who are less familiar with digital technology may benefit from personalised training to facilitate effective use of the app. The current user guide could be further expanded to provide more comprehensive explanations of the app's functions. For users who continue to experience difficulties, a dedicated support helpline may also be offered.

# 8.8 Conclusion

## 8.8.1 Key Achievements

This thesis describes the development and initial feasibility testing of a mobile app and a web portal to facilitate home-based CR within a single NHS trust. An ML model was developed to automate exercise prescriptions for cardiac patients, which was subsequently used in a clinical trial to deliver home-based CR for the first time in the NHS, with accelerometer-guided real-time activity monitoring.
In this study, we demonstrated that it is feasible to conduct a larger-scale RCT to assess the effectiveness of a home-based CR programme. We also illustrated that the mobile app was highly usable and acceptable to participants. However, significant methodological refinements will be required to develop a validated ML model.

This project may also encourage clinicians to adopt an active role in developing digital health innovations with less reliance on commercial developers.

## 8.8.2 Future Vision

We propose a larger definitive RCT to assess the effectiveness of an AI-powered, mobile app-facilitated home-based CR programme. A larger RCT would also allow researchers to collect more data to build a better ML model.

A home-based programme facilitated by a mobile app and automated exercise prescription may also be used in other areas of medicine, including pulmonary and stroke rehabilitation (369, 370).

The mobile application can be further improved to allow patients to directly message and video call HCPs, allowing staff based at the hospital to view and respond to these messages via the web portal.

# 9. Appendix

## Appendix A Search Strategy Systematic Review

Medline

app.ab,ti. and (cardiac.ab,ti or cardiac rehabilitation/) and (rehabilitation.ab,ti or cardiac rehabilitation/ or telerehabilitation/ or telerehabilitation.ab,ti.)

Embase

cardiac.ab,ti. and (app.ab,ti. or mobile application/) and (rehabilitation.ab,ti. or heart rehabilitation/ or home rehabilitation/ or telerehabilitation.ab,ti. or telerehabilitation/)

CINAHL

(MH “Mobile Applications”) and ((MH “Rehabilitation, Cardiac”) OR “cardiac”) and ((MH “Rehabilitation”) or “rehabilitation” or (MH “Home Rehabilitation”) or (MH “Rehabilitation, Cardiac”) or (MH “Telerehabilitation”) or “telerehabilitation”)

# Appendix B Risk of bias assessments Systematic Review

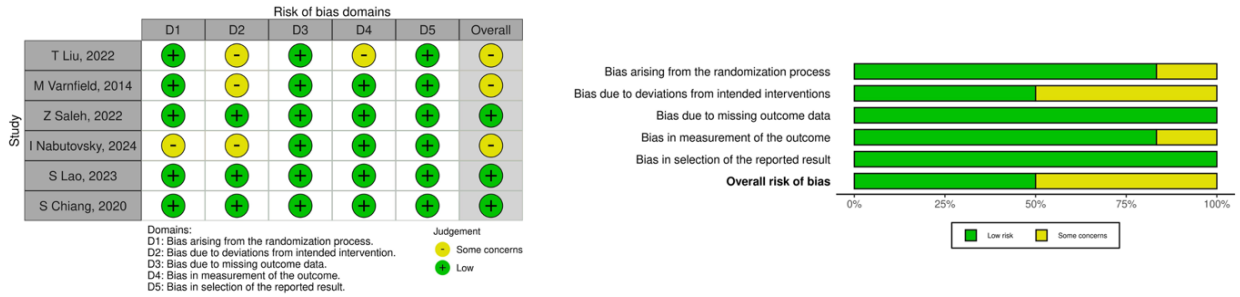



*Figure 2 Risk of bias assessment ROB2*

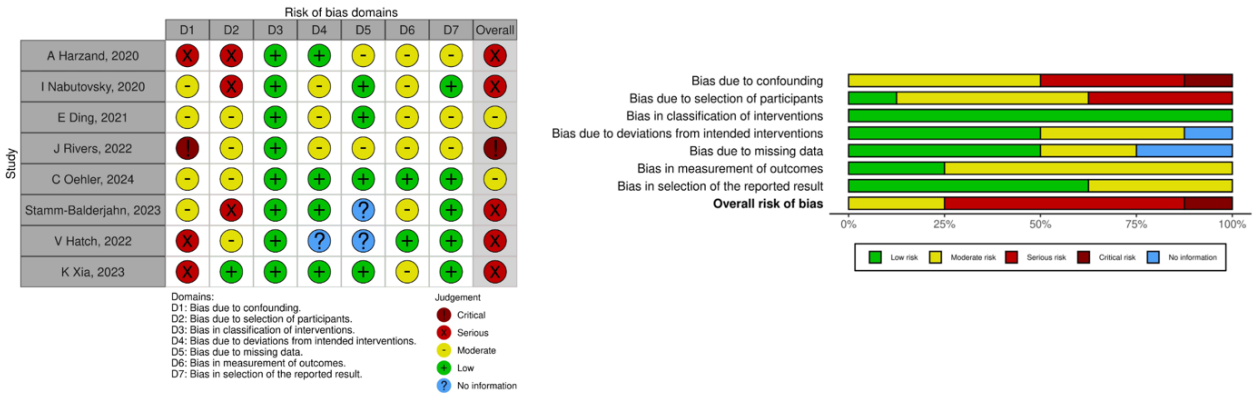



*Figure 3 Risk of bias assessment ROBINS I*

Appendix

| | Newcastle-Ottawa Quality Assessment Score | | | |
|---|---|---|---|---|
| **Study** | Selection Score | Comparability Score | Outcome Score | AHRQ Conversion |
| **N Freene, 2020** | 3 | 1 | 2 | Fair |
| **A Sengupta, 2020** | 3 | 1 | 2 | Fair |
| **A Beatty, 2018** | 3 | 0 | 0 | Poor |
| **Z Saleh, 2023** | 2 | 0 | 2 | Poor |
| **Y Son, 2022** | 2 | 0 | 2 | Poor |

*Figure 4 Risk of bias assessment Newcastle-Ottawa Quality Assessment Score*

# Appendix C Ethics Approval Letter

Prof Enoch Akowuah
James Cook University Hospital Marton Rd, Middlesbrough
TS4 3BWN/A
Email: approvals@hra.nhs.uk

05 September 2022 Dear Prof Akowuah

**HRA and Health and Care Research Wales (HCRW) Approval Letter**

| | |
|---|---|
| **Study title:** | **Rehabilitation through Exercise prescription for Cardiac patients using an Artificial Intelligence based Programme - RECAP** |
| **IRAS project ID:** | **315483** |
| **Protocol number:** | **N/A** |
| **REC reference:** | **22/SC/0262** |
| **Sponsor** | **South Tees Hospitals NHS FT** |

I am pleased to confirm that **HRA and Health and Care Research Wales (HCRW) Approval** has been given for the above referenced study, on the basis described in the application form, protocol, supporting documentation and any clarifications received. You should not expect to receive anything further relating to this application.

Please now work with participating NHS organisations to confirm capacity and capability, in line with the instructions provided in the "Information to support study set up" section towards the end of this letter.

### 4. How should I work with participating NHS/HSC organisations in Northern Ireland and Scotland?

HRA and HCRW Approval does not apply to NHS/HSC organisations within Northern Ireland and Scotland.

If you indicated in your IRAS form that you do have participating organisations in either of these devolved administrations, the final document set and the study wide governance report (including this letter) have been sent to the coordinating centre of each participating nation. The relevant national coordinating function/s will contact you as appropriate.
Please see IRAS Help for information on working with NHS/HSC organisations in Northern Ireland and Scotland.

### 5. How should I work with participating non-NHS organisations?

HRA and HCRW Approval does not apply to non-NHS organisations. You should work with your non-NHS organisations to obtain local agreement in accordance with their procedures.

### 6. What are my notification responsibilities during the study?

The standard conditions document "*After Ethical Review – guidance for sponsors and investigators*", issued with your REC favourable opinion, gives detailed guidance on reporting expectations for studies, including:

- Registration of research
- Notifying amendments
- Notifying the end of the study

The HRA website also provides guidance on these topics, and is updated in the light of changes in reporting expectations or procedures.

### 7. Who should I contact for further information?

Please do not hesitate to contact me for assistance with this application. My contact details are below.

Your IRAS project ID is **315483**. Please quote this on all correspondence. Yours sincerely,

Benita Hallewell-Goodwin

Email: approvals@hra.nhs.uk

*Copy to: Mr Joe Millar, South Tees Hospitals NHS Foundation Trust*

**8. List of Documents**

The final document set assessed and approved by HRA and HCRW Approval is listed below.

| *Document* | *Version* | *Date* |
|---|---|---|
| GP/consultant information sheets or letters [GP Notification Letter] | 1.0 | 11 July 2022 |
| Interview schedules or topic guides for participants [Topic Guide Participants] | 1.0 | 11 July 2022 |
| Interview schedules or topic guides for participants [Staff Focus Group Topic Guide] | 1.0 | 11 July 2022 |
| IRAS Application Form [IRAS_Form_12072022] | | 12 July 2022 |
| Letters of invitation to participant [Invitation Letter] | 1.0 | 11 July 2022 |
| MHRA Notice of No Objection Letter (Medical Devices) and relevant correspondence | | 23 December 2022 |
| Non-validated questionnaire [Patient Questionnaire] | 1.0 | 11 July 2022 |
| Participant consent form [Consent Form] | 2.0 | 30 August 2022 |
| Participant consent form [Tracked_Consent Form] | 2.0 | 30 August 2022 |
| Participant information sheet (PIS) [PIS Phase I] | 1.0 | 08 July 2022 |
| Participant information sheet (PIS) [PIS Phase II] | 2.0 | 30 August 2022 |
| Participant information sheet (PIS) [Tracked_PIS Phase II] | 2.0 | 30 August 2022 |
| Participant information sheet (PIS) [PIS Phase I] | 2.0 | 30 August 2022 |

Appendix

| | | |
|---|---|---|
| Participant information sheet (PIS) [Tracked_PIS Phase I] | 2.0 | 30 August 2022 |
| Research protocol or project proposal [Protocol] | 1.0 | 11 July 2022 |
| Summary CV for Chief Investigator (CI) [CV of CI] | | 11 July 2022 |
| Summary CV for student [Student CV] | | 11 July 2022 |
| Summary CV for supervisor (student research) [Supervisor CV] | | 12 July 2022 |
| Validated questionnaire [HADS] | | |
| Validated questionnaire [PROM CR] | | |
| Validated questionnaire [Rockwood Scale] | | |
| Validated questionnaire [Barthel Index] | | |
| Validated questionnaire [SF36] | | |
| Validated questionnaire [EQ-5D-5L] | | |
| Validated questionnaire [MAUQ] | | |
| Validated questionnaire [SUS] | | |

# Appendix D RECAP RCT Study Protocol

## 9. Glossary of Abbreviations

**AE** – Adverse event

**AI** – Artificial Intelligence

**CABG** – Coronary Artery Bypass Graft

**CHD** – Coronary Heart Disease

**GCP** – Good clinical practice

**HADS** – Hospital Anxiety and Depression Scale

**HBCTR** - Home-based cardiac telerehabilitation

**ML** – Machine Learning

**MAUQ** – mHealth App Usability Questionnaire

**NoSQL** - No Structured Query Language

**UI** – User Interface

**UX** – User experience

**SAE** – Serious adverse event

**SUS** - System Usability Scale

**SDV** - Source data verification

**6MWT** – 6-minute walk test

## Introduction

## Lay Summary

Increasing physical activity after a heart attack or a heart operation can help improve fitness levels and help patients return to normal activities more quickly.

Traditionally this has been done in hospitals in the form of rehabilitation classes. Most hospitals offer these classes to patients. The sessions are conducted by a health care professional with specific training, and patients attend the hospital every week to take part. However, some patients may not be able to attend sessions due to practical reasons, such as the availability of transport. Patients may also be fearful of exposure to infections by going into hospitals or any other community spaces.

As we emerge from the Covid-19 pandemic, it is clear that new ways of working that reduce the need for patients to come to the hospital are urgently needed. The NHS long-term plan for the NHS has committed to moving services into the community wherever possible. It would be ideal if we can move rehabilitation from the hospital to the home.

However, there are challenges to being able to do this successfully, including in communicating effectively with patients, monitoring what they are doing, and adapting the rehabilitation programme to respond to their needs in a timely way.

In this study, we want to work out if we can use new technologies to help us deliver safe and effective rehabilitation at home.

Appendix

We will test a home-based rehabilitation system that uses devices that patients can wear on their wrists. The devices, known as accelerometers, can help us monitor patients' activity levels as they go about their day. It captures information such as their step count and how many calories they use. We will use this information to set goals for each patient based on their own activity levels. At first, a healthcare professional will set these goals. Later, we will set these goals automatically using a computer system.

Patients will have access to a mobile phone application on which they will receive their weekly target goals. Once they achieve these, the application will automatically mark it as complete. We will also develop a web portal to allow the rehabilitation team to remotely monitor patients' activity levels, and a computer system to prescribe exercises to each patient.

We will then do a feasibility trial that will compare traditional classes with the home-based exercise system to see the impact of the home-based rehabilitation programme compared to the hospital-based setting. We will see if there is an improvement in patients' fitness levels by comparing how far they can walk in six minutes before and after the programme. We will also see whether the home-based programme increases the proportion of eligible patients who complete the rehabilitation programme and test a number of other elements to confirm this is feasible. If the results show that it is, we will use the information to plan a larger trial to confirm our findings.

Appendix

**Background and rationale**

Cardiovascular disease is the leading cause of death worldwide. There are around 7.6 million people living with cardiovascular disease in the United Kingdom (UK). Coronary heart disease (CHD) is the most common form of cardiovascular disease. [3]

Modification of cardiovascular risk factors has been shown to reduce the morbidity and mortality associated with CHD.[11] As part of The American Heart Association's (AHA) 'Strategic Impact Goal Through 2020 and beyond', a new model of assessing cardiovascular health based on seven risk factors was developed. The AHA goals include the following seven behaviours and risk factors (Life's Simple & metrics): smoking status, body mass index, physical activity, healthy dietary score, total cholesterol, blood pressure, and fasting plasma glucose. Studies have shown that people with at least five ideal Life's Simple 7 metrics had a 78% reduced risk of heart-related death compared to people with no ideal metrics [2].

Cardiac rehabilitation programs have been shown to be very effective in improving functional capacity[14] and reducing readmission rates[12] after cardiac surgery. It can also benefit the participants in the long term. Postoperative patients with higher physical activity levels also had fewer subsequent cardiovascular events [12] and lower mortality at 10 years [13].

The European Society of Cardiology (ESC) guidelines for stable cardiovascular patients, strongly recommend secondary prevention including participating in comprehensive cardiac rehabilitation (CR) [4]. However, despite the numerous benefits of CR, uptake is low[19]. In the EUROASPIRE III survey, 44.8% of patients were advised to attend a CR programme after a coronary event or revascularisation. Out of these, only 81.4% did so. This accounts for 36.5% of all patients that were potentially eligible [5]. Participation may be improved by inviting a greater proportion of patients to attend a CR programme, and potentially through providing rehabilitation remotely.

The NHS long-term plan focuses on providing digitally enabled primary and outpatient care while supporting the development of applications and online resources to enable recovery [15].

One of the aims is to reduce face-to-face outpatient visits by up to one third over the next five years by redesigning services [15].

Over the last few years, there has been an increasing interest in providing rehabilitation programmes remotely. During the COVID-19 pandemic, several hospitals have achieved this. Many patients may prefer home based rehabilitation due to convenience and hesitancy to attend a hospital due to the risk of infection[19]. A systematic review and meta-analysis [6] looking at home-based cardiac telerehabilitation (HBCTR) vs usual care concluded that HBCTR was associated with an increase in functional capacity, physical activity, and reduced depression when compared with usual care. This study included patients over the age of 18, with a diagnosis of coronary heart disease, acute coronary syndrome or patients who had undergone coronary artery bypass graft surgery.

### 3.3 Accelerometers

Accelerometers offer a valid, non-invasive method of measuring physical activity under normal living conditions. These are small, lightweight wearable devices with low operating costs. For this project, we will be using the CentrePoint Insight Watch by Actigraphcorp. This is a triaxial accelerometer which measures accelerations in the anteroposterior, mediolateral and vertical direction. It will be worn by the participant around their wrist. This device is capable of wirelessly transmitting the captured data into a remote cloud, enabling remote monitoring of physical activity by a clinical team.




*Figure 26 Actigraph Accelerometer*

### 3.4 Hospital-Based Rehabilitation Programme

It is recommended that hospital-based cardiac rehabilitation is offered to all patients following cardiac surgery, elective coronary angioplasty and stent insertion, percutaneous coronary intervention, myocardial infarction, angina and heart failure. NICE guidelines recommend that patients should be provided with a range of options within a rehabilitation programme[24]. These patients should be offered a cardiac rehabilitation pre-assessment clinic appointment following discharge. The date of the appointment will depend on the diagnosis as outlined in the table below

| Diagnosis | Timing of preassessment clinic appointment following discharge |
|---|---|
| **Cardiac surgery** | 5-6 weeks |
| **- Elective coronary angioplasty and stent insertion**<br>**-Percutaneous coronary intervention (PCI)** | 1-2 weeks |
| **Myocardial infarction** | 1-2 weeks |
| **Angina** | As soon as possible following diagnosis |

During the pre-assessment appointment (which usually lasts about one hour) the patient is seen by a cardiac rehabilitation nurse and an exercise professional. During the appointment, the patients' fitness levels will be assessed, and they will have the opportunity to set diet and exercise goals.

The formal exercise programme takes place at the hospital with exercise classes, once a week, for eight weeks. Each session lasts two hours and is conducted by an exercise professional and a rehabilitation nurse.

As part of this project, we will evaluate a remote rehabilitation programme that takes place at the patient's home.

### 3.5 Home-based rehabilitation

Currently, patients who are not able to attend hospital-based exercise classes are provided with an exercise booklet and are advised to exercise at home. However, the hospital does not have a way of monitoring these patients. In keeping with the NHS long term plan, developing a home-based exercise programme where we could monitor the patients, offers opportunities for patient engagement, improved outcomes for patients through increase uptake of the programme, and could be cost-effective for the NHS.

### 3.6 Intervention Development (Home-based rehabilitation system)

We will use accelerometers to monitor the impact of a **Home-Based Rehabilitation system**.

Patients will wear the accelerometer devices as part of the clinical trial. This will allow us to track their physical activity levels in almost real-time.

**We will**:

- Create a rehabilitation app for patients to use (rehab app)
- Develop a machine learning algorithm to generate personalised exercise goals
- Create a web portal for hospital staff to remotely monitor patients' activity levels

The **Rehab app** will receive data from the accelerometers which it will then feed to the machine learning algorithm, to get the generated goals. Patients will be able to view their weekly goals on the app. The generated goals will be in the following domains:

- Calorie count
- Step count
- Number of minutes spent in moderate to vigorous physical activity (MVPA)

To provide a structure, we will provide each patient with an exercise booklet that contains numbered exercises. We will work with the physiotherapy department at the James Cook University Hospital to develop a series of exercise videos to accompany the booklet. When the weekly goals are generated and displayed on the app, it will also display a series of

recommended exercises based on the target parameters. These exercises will be selected from a pool of exercises, based on the progress of the patient.

The patient activity levels will be recorded by the accelerometer devices and uploaded to the remote cloud. This will happen through the **Actigraph app** which will be installed on patients' phones along with the **Rehab app**. The data will be automatically uploaded at set intervals. This data will then be retrieved by the Rehab App.

The password-protected **web portal** will only be accessible by staff via the internet. It will display all the patients involved in the trial and allow them to see if each patient is achieving their target goals. The website will not contain any patient identifiable information. Each participant will be identified by their unique study ID.

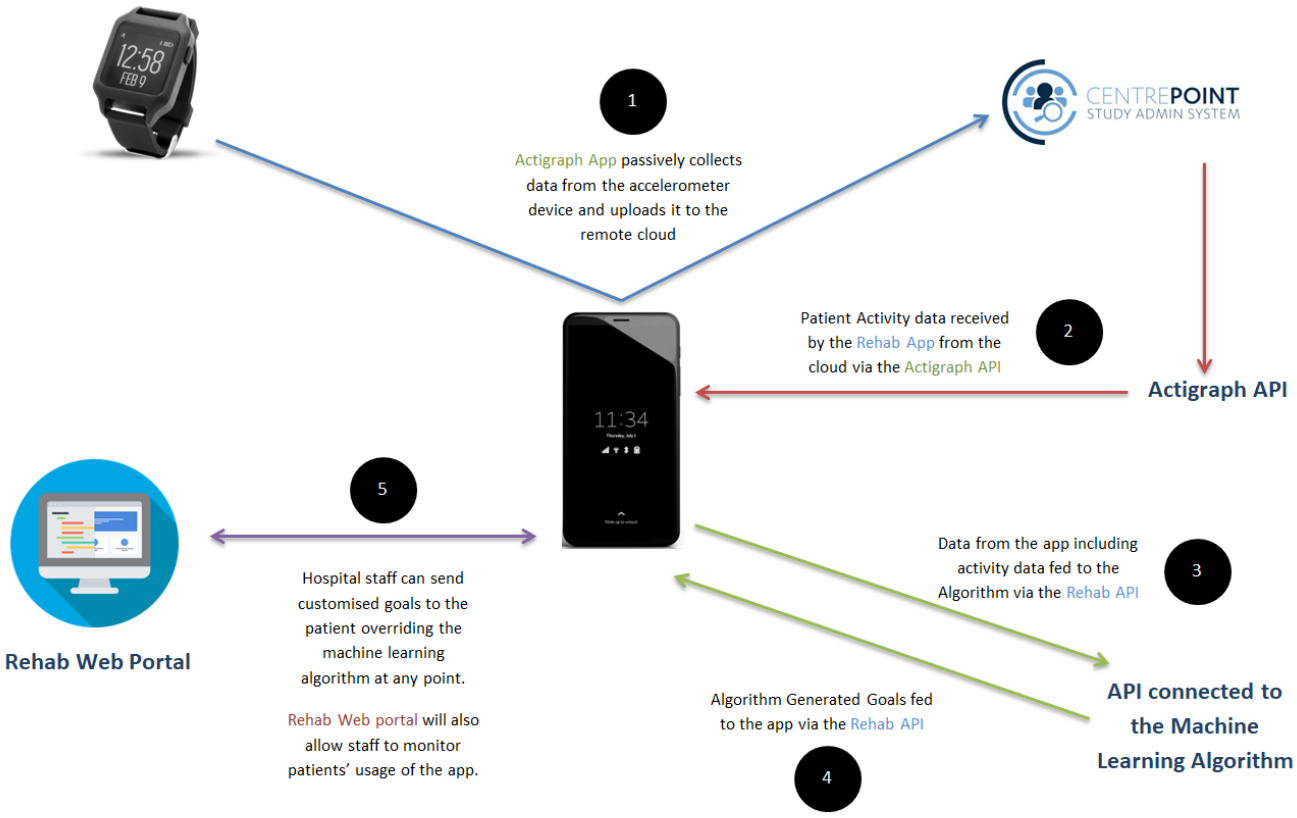



*Figure 2 Diagram showing an overview of the stages in the intervention*

As far as we are aware, there have been no telerehabilitation programmes that use machine learning to offer a fully automated home-based rehabilitation service.

### 3.7 Study Overview

**We will develop and test the intervention in a two-stage project. Phase I will be a usability study and phase II will be a feasibility randomized controlled trial.**

Phase I is expected to last six months, following which Phase II will start, with time built in to accommodate the findings from phase I.

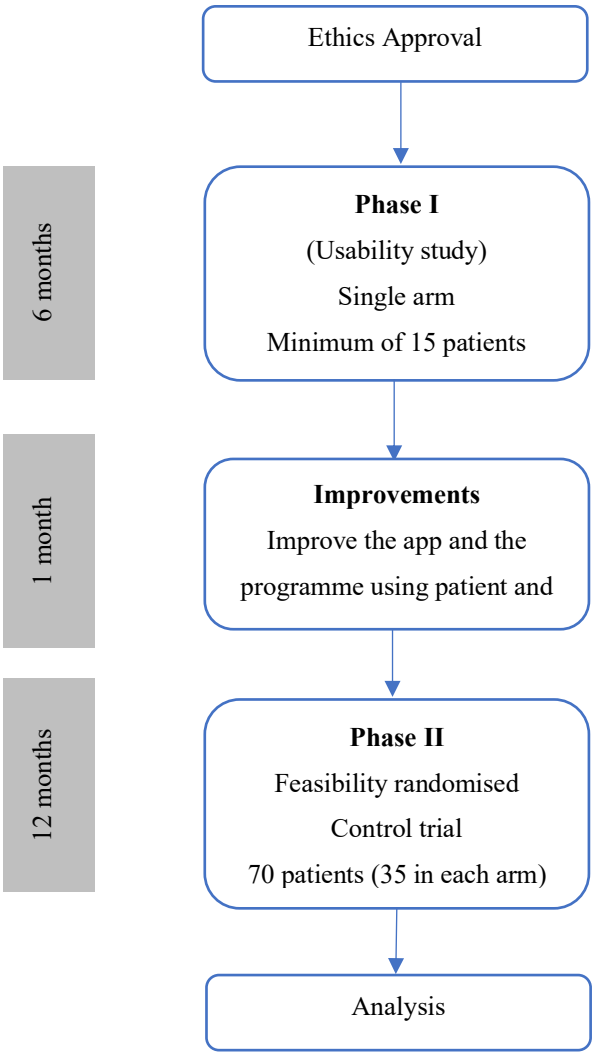



*Figure 3 Study overview*

Appendix

**Phase I Usability Study**

In this Phase I usability study, patients will take part in the home-based rehabilitation programme wearing the accelerometers.

**Phase I Research Question / Aims**

**The objectives include**:

- Assess functioning of the accelerometers and the app
- Check the functioning of the web portal and communication with the devices including sending custom notifications and setting custom goals to patients
- Collect qualitative data on participant and staff experience of the programme using structured interviews and/or focus groups.
- Make any necessary changes to the app and the web portal using the data collected
- Test the feasibility of patients' interactions with the app including ease of use, technical support, adherence etc

**Phase I Sample size**

In **Phase 1**, we will test the intervention (app and accelerometers) on a minimum of 15 patients that match the inclusion criteria given in section 5.3.2.

Participants will take part in the programme for eight weeks. This sample size is not based on a power calculation as Phase I is intended to allow us to test the technology and the programme before we commence Phase II. We have estimated that 15 patients will allow us to gather all the data we need.

**Phase I Recruitment**

Recruitment and study assessments will be done as outlined in section 5.4. However, phase I will be a single-arm study (home-based rehabilitation) without a control arm.

The study is expected to take 6 months.

**Phase I Structured Interviews**

We will conduct structured interviews to find out about the patient experience in the programme. The data we collect from phase one will be used to better inform phase two which is the feasibility randomised control trial.

We will also gather data on the experience of the staff members who took part in the study using focus groups and/or structured interviews. As part of the programme, the staff will use the online web portal to monitor the patients, view their activity levels, send custom notifications, and set custom goals where appropriate.

Staff interviews and/or focus groups will take place at the hospital and/or conducted via telephone or online virtual meeting platforms, and patients will be contacted via telephone. Patient interviews may also be conducted during their final visit. We will aim to interview all patients that took part in Phase I, or until we have reached data saturation. Patients will be consented for structured interviews during the initial consent.

**Learning from Phase I**

We will collect feedback on the app, the web portal, and the home-based exercise programme and address any technical issues, and make modifications based upon feedback before we move on to phase II.

- Feedback on the app from questionnaires and structured interviews with patients
- Feedback on the web portal from staff interviews / focus groups
- App usage analytical data will be collected automatically

**Data collection in Phase I**

The data collected will be the same in both Phase I and Phase II, as outlined in Summary of Study Assessments (Phase I and II). The data will be collected by the rehabilitation team and the study team at the baseline and final visit. The data collected in Phase I will allow us to

further train the machine learning algorithm that will be used to generate exercise prescriptions. This will be important learning as more data points will result in better exercise prescriptions (generated goals from the algorithm).

**Feasibility Randomised Control Trial (Phase II)**

We will perform a single centre randomised clinical trial. The study will recruit patients that are eligible for cardiac rehabilitation (post-ACS and cardiac surgery) at the James Cook University Hospital Middlesbrough, into two groups:

- Traditional hospital-based exercise rehabilitation programme (control group)

- Home based rehabilitation using accelerometer devices and mobile phone application (intervention group)

**Research Question / Aims (Phase II)**

**Aim**: to conduct a feasibility study to evaluate the safety and effectiveness of home-based cardiac rehabilitation using accelerometer devices and a mobile phone application

In the development and deployment of a new intervention, several criteria need to be assessed. Both short term and long-term effects must be considered [1]. We will assess the feasibility of this intervention. In order to do this, we will assess the participants' and health care practitioners' satisfaction, the intent to continue use, perceived appropriateness and fit within the organizational culture [18]

**Primary objective (Phase II):**

This project aims to establish the feasibility of conducting a large-scale randomised control trial. The objectives include:

- Evaluate participant recruitment rates and dropout rates
- Feasibility of randomisation

- acceptability to the participants, the rehabilitation team, and the hospital as an organisation
- determine outcome measures for the larger RCT
- determine hospital resource allocation to inform a full economic evaluation
- collect outcome data for power and sample size calculations for RCT
- collect data to inform a better machine learning algorithm capable of prescribing realistic exercise goals

**Secondary objectives (Phase II):**

The secondary objectives of this study are as follows:

- To assess the impact of the intervention on patient's physical fitness using the 6-minute walk test
- To evaluate the feasibility and acceptability of the intervention by assessing the participants' and health care practitioners' satisfaction, the intent of continue use, perceived appropriateness and fit within the organizational culture [18]
- To assess engagement measured by the daily number of active users of the app and software analytics
- To evaluate the impact of the intervention on the health-related quality of life using the EQ-5D-5L scale, and SF-36 questionnaire
- To evaluate performance in activities of daily living (ADL) using the Barthel Index
- To conduct a qualitative process evaluation to identify barriers and enabling factors of this intervention
- Explore health motivators of behaviours using the information gathered via the app and Hospital Anxiety and Depression Scale assessed at the beginning and end of the intervention
- To assess frailty using Rockwood scale [21]
- To assess impact on their quality of life using the PROM-CR questionnaire
- To evaluate the usability of the app using system usability scale questionnaire (SUS) and mHealth App Usability Questionnaire (MAUQ)
- To inform the design of a larger clinical trial to demonstrate the impact and cost effectiveness of a fully automated remote rehabilitation system

## 5.2 Study Setting and duration (Phase II)

The study will be conducted at a single NHS centre, The James Cook University Hospital. The total duration of this study (for phase I and phase II) is anticipated to be 18 months. We will recruit a minimum of 15 patients in phase I and 70 patients in phase II (randomised into two arms). The final 3 months of the study will consist of data collection, cleaning, and analysis.

## 5.3 Participants (Phase I and II)

### 5.3.1. Overall Description of Trial Participants

Patients eligible for cardiac rehabilitation at the James Cook University Hospital will be screened for potential eligibility and invited to take part by members of the clinical team.

### 5.3.2. Inclusion and Exclusion criteria (for both Phase I and II)

**Inclusion criteria**

- Patients post-cardiac surgery and post-acute coronary syndrome who have been referred for cardiac rehabilitation
- Age 18 and over
- Have access to an Android or iOS mobile device
- Provided informed consent

**Exclusion criteria**

- Awaiting urgent surgery
- Unstable angina
- Pregnancy
- Currently enrolled in another interventional clinical trial or experiment where the intervention is considered likely to impact the outcomes of RECAP trial
- Malignant arrhythmias
- Contraindications to rehabilitation

- Severe musculoskeletal conditions affecting exercise ability
- Acute systemic illness or fever
- Acute pericarditis or myocarditis
- Uncontrolled atrial or ventricular arrhythmias
- Uncontrolled sinus tachycardia
- Aortic stenosis associated with pre-syncope / syncope
- Uncompensated Heart failure
- Complete atrioventricular block without a pacemaker
- Recent embolism

Patients who agree to take part will be asked to sign a consent form. Those providing consent and confirmed to be eligible in Phase I will progress to CR. Those providing consent and found to be eligible in Phase II will then be randomised in a 1:1 ratio to either control (hospital-based cardiac rehab) or intervention (home-based cardiac rehab with accelerometer data-driven goal setting).

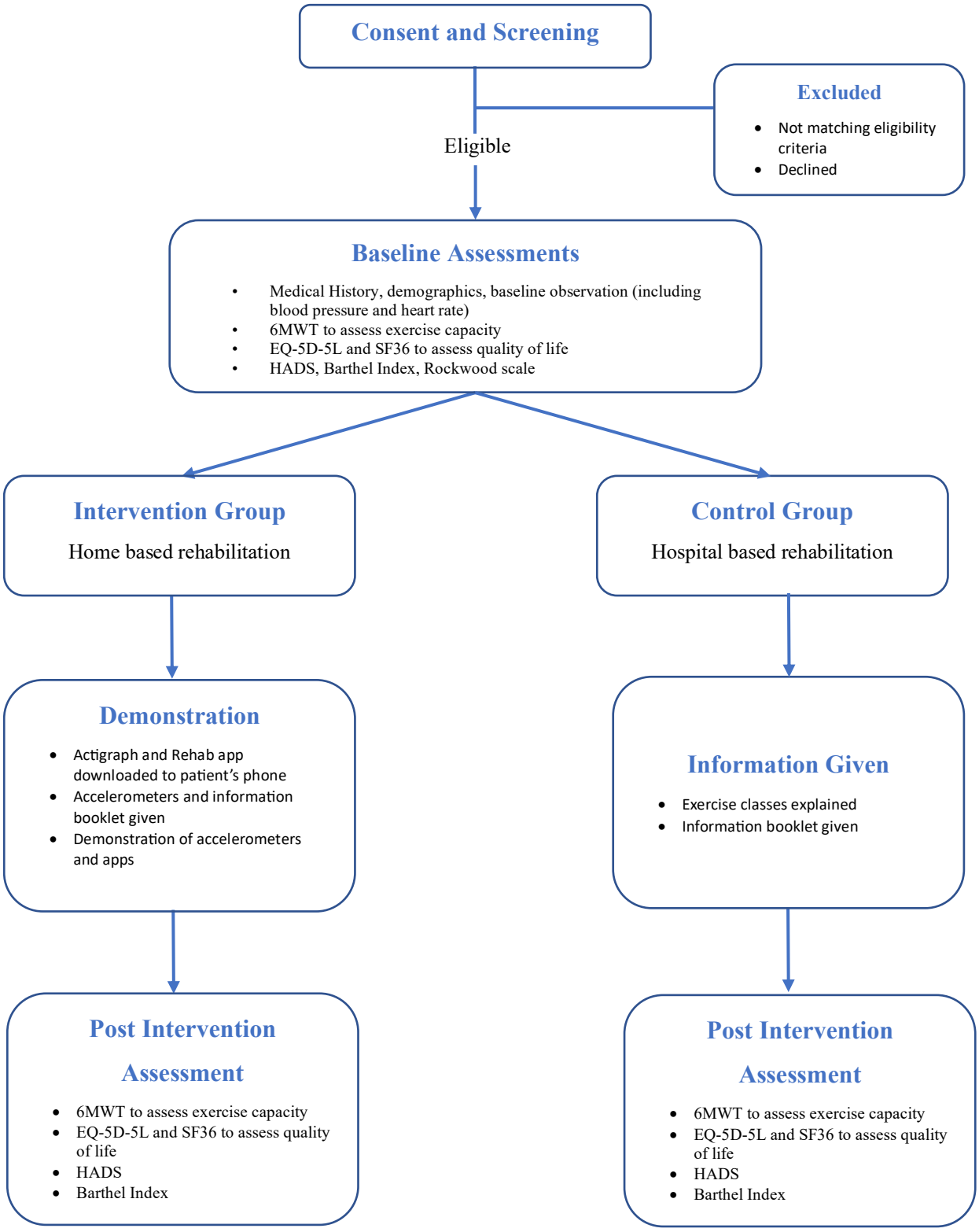
### 5.3.3 Study duration (Phase II)

The randomised trial is anticipated to take 10 months, with recruitment expected to end during month 8.

Appendix

### 5.3.4 Randomised Control Trial Flow Diagram (Phase II)

The last stage of the study will be done as a clinical trial – stages are as shown below.



**Recruitment (Phase I and II)**

**Screening and Eligibility Assessment**

Patients are routinely reviewed in the outpatient rehabilitation clinic following discharge. The rehabilitation team will identify patients who match the study criteria at this point. The patients will be given an information sheet and introduced to the study. Where possible, the information sheet will be posted to the patient before the outpatient clinic appointment. Patients who express an interest in this study will have the opportunity to ask any questions. Patients who decline will be asked if they are willing to provide the reason for this and this information will be used to understand barriers to recruitment to inform future studies.

A digital electronic screening form will be completed to confirm the patients who meet the inclusion criteria. We will record the following:

- Name
- Hospital number
- Capacity to provide informed consent
- Contact number

**Informed consent (Phase I and II)**

Wherever possible, participant information sheets (PIS) and a letter of invitation will be sent to potentially eligible patients by the clinical team prior to their preassessment rehabilitation clinic appointment, this may be by email as per local trust policy. Where patients do not receive the PIS or letter of invitation prior to their clinic appointment, the rehabilitation team, the research team or a clinician may discuss the trial with the patient, and provide the PIS and invitation letter during the clinic. All patients will be given sufficient time to read the PIS, discuss the trial and have any questions answered by the clinical team at this appointment. The PIS will explain the nature of the trial and any risks involved in taking part. It will be clearly stated that the participant is free to withdraw from the trial at any time for any reason without prejudice to future care, and with no obligation to give the reason for withdrawal.

The patient will be encouraged where possible to discuss the trial with their family or friends (or other independent parties) to decide whether or not to participate in the trial.
Participants who meet the eligibility criteria and decide to take part will be asked to provide written informed consent. This will be obtained by means of participant's dated signature and the dated signature of the person who obtained the informed consent. The person who obtained the consent will be a suitably qualified and experienced member of the research team and have been authorised to do so by the Chief/Principal Investigator. Copies of the signed Informed Consent will be given to the participants as well as filed in the medical notes. The original signed form will be retained in the study file.
The participant must sign, print their name and date the latest approved version of the informed consent form before any trial-specific procedures are performed. If for whatever reason the patient is unable to print their name or date on the consent form this can be completed by the researcher taking consent, at the patient's request. It must be fully documented on the consent form that the researcher has taken this action, with the reason why also documented. However, the researcher must NOT sign the consent form on behalf of the patient; the patient must always sign the consent form.
Participants may also be asked to provide informed consent by post or via digital means.

**Baseline assessments (Phase I and II)**

These assessments will be performed after consent and, in Phase II, prior to randomisation. The baseline assessments will consist of the 6MWT, EQ5D5L and SF36 questionnaire, HADS, and Barthel Index questionnaire. The participants' medical notes will be used to collect a full medical history, sex, and date of birth/age. They should have a recent recording of the participant's height and weight; if this is not present a new measurement should be taken and recorded in the notes.
All participants in Phase I and participants in the intervention arm of Phase II will be given an accelerometer and assisted to download the applications onto their mobile devices. We will also give them an information sheet on how to use the app and the accelerometers following a demonstration.

**Randomisation (Phase II)**

Subject identification numbers will be assigned as per the patient screening log for patients in both Phase I and Phase II. Eligible participants will be randomised on a 1:1 ratio to either the intervention arm (home-based rehabilitation) or the control arm (standard care only) to reduce the risks of selection bias.

Randomisation will be performed by delegated and trained members of the research team at JCUH.

Randomisation will be performed using block randomisation with stratification.
It will not be possible to conceal the allocation of treatment from the participant or the team delivering the intervention and measuring the primary outcome.

**Assessment Time Points**

Research assessments will be carried out at routine clinical appointments wherever possible. If this is not possible additional research visits will be made at a time convenient to the participant. Baseline assessments will be completed at the pre-assessment clinic appointment and final assessments will be completed post-rehabilitation after 8 weeks have been completed.

**Discontinuation/ Withdrawal of Participants from Trial Treatment**

Each participant has the right to withdraw from the trial at any time. In addition, the investigator may discontinue a participant from the trial at any time if the investigator considers it necessary for any reason including:

- Ineligibility (either arising during the trial or retrospectively having been overlooked at screening)
- An adverse event, which results in the inability to continue to comply with trial procedures
- Consent withdrawn
- Pregnancy

Participants who have been randomised to the intervention arm in Phase II, or who take part in Phase I will also have the option of attending standard rehabilitation classes if for any reason they do not want to continue with the intervention (home-based rehabilitation programme).

Participants who wish to withdraw consent for the trial or whose participation from the trial is discontinued will have pseudonymised data collected and analysed up to the point of that withdrawal. No additional data will be collected from the participant unless they have specifically consented to continue routine clinical outcome data collection and this is documented in the medical notes.

Clinicians or participants may decide that they should no longer perform certain parts of the trial intervention or assessments, in these cases participants will continue in the trial and any assessments not completed will be treated as missing data. The reason for withdrawal will be recorded in the CRF. Participants who withdraw once they have been randomised will not be replaced. Participants found to be ineligible after randomisation will be withdrawn with no further data collected after that point. If the participant is withdrawn due to a related (definitely, probably, and possibly related) adverse event, the investigator will arrange for follow-up visits or telephone calls until the adverse event has resolved or stabilised. Adverse events that are not related to the intervention will be followed up to the point of trial completion.

**Trial Intervention**

**Standard Care**

Patients in this group will follow the hospital-based rehabilitation programme. They will attend exercise classes at the hospital, once a week, for 8 weeks. They will not take part in any home-based exercise programme.

**Home-based Exercise Programme**

Appendix

Patients in this group will follow an 8-week home-based exercise programme. They will be given an exercise booklet which will outline a series of exercises with varying difficulty, and an accelerometer to take home. They will also be given weekly goals via the app in the domains of step count, calorie count and moderate to vigorous activity minutes.

Patients randomised to this group will follow the home exercise programme. The programme will consist of:

- Initial fitness assessment at the hospital
- Home-based exercise programme guided by exercise videos and exercise booklet. Patients will be given weekly goals via their mobile app.

**Summary of Study Assessments (Phase I and II)**

**These assessments will be the same for both phase I and phase II.**

| Procedures | Visits | |
|---|---|---|
| | Baseline visit | Final visit |
| **Talk to the patient about the study and answer any questions** | X | |
| **Check Eligibility** | X | |
| **Obtain written Informed Consent for participation (may be done by post or via digital means as well)** | X | |
| **Medical History** | X | |
| **Demographics** | X | |
| **Physical assessment of height, weight, blood pressure and baseline observations** | X | X |
| **Assessment of 6-minute walk test, frailty score (Clinical Frailty Scale / Rockwood scale)** | X | X |
| **EQ-5D-5L, SF-36, Barthel Index and HADS score calculation** | X | X |
| **System Usability Scale (SUS) questionnaire and mHealth App Usability Questionnaire (MUAQ)** | | X |

Appendix

| | | |
|---|---|---|
| **Adverse event evaluation** | | X |

**Initial Assessment (Phase I and II)**

At the initial cardiac rehabilitation assessment clinic visit, participants will be assessed by a cardiac rehabilitation specialist to gauge their physical fitness involving:
Subjective assessment of:

1. General wellbeing
2. Recent health issues and medical history
3. Fitness and activity levels
4. Anxiety levels
5. Social circumstances and support

Social circumstances will include partner status, education status, and employment status. This information will be required by the machine learning algorithm to generate the weekly exercise predictions. The dataset used to train the algorithm uses this information for the prescriptions.

Objective assessment of:

1. Heart rate, blood pressure, Oxygen saturation and respiratory rate
2. ECG if indicated
3. Respiratory function (breathing pattern and auscultation with stethoscope)
4. Musculoskeletal system (joint range and muscle strength)
5. Other physical problems
6. Mobility, gait and balance

**Home Exercise Programme**

Patients will be advised to do up to 45 minutes of exercise at home (unsupervised) up to 7 times a week during the 8-week period. The rehabilitation team will advise them on the type of exercises to follow based on their initial assessment of physical fitness and the baseline

6MWT. They will be advised to exercise to achieve a moderate BORG Score. The BORG scale is a way of measuring physical activity intensity level.

The rehabilitation team will be able to monitor the patient's progress using the web portal. The web portal will allow a healthcare professional to:

- View the daily step count, calorie expenditure and moderate to vigorous physical activity minutes, of the participant
- View the goals that have been set on a week-by-week basis
- Send custom notifications to each participant
- Set custom goals for each participant

Patients will be contacted via phone if they do not meet the predefined minimal adherence criteria (not opened the app for 5 consecutive days), or if issues arise that indicate concern to the clinical team.

If a participant decides not to continue with the home exercise programme, they will be given the option to attend standard hospital-based rehabilitation classes.

**End of Intervention**

At the end of the rehabilitation programmes (both home-based and in-hospital), the patients will attend the hospital for the assessment of their physical fitness and complete the end-of-intervention questionnaires. Those patients who consent to take part in the qualitative research (structured interviews), will also be contacted by phone to find out about their experience of the programme. These interviews may also be conducted during their final visit. This will mark the end of the intervention.

**Assessment of Compliance**

Accelerometer wear time and app usage data will be used to assess compliance with the intervention.

**Safety Reporting (Phase I and II)**

**Potential risks**

Home based rehabilitation is already in common use. [22] Telerehabilitation can offer a safe solution for patients who are not able to attend the hospital and there are guidelines on how to optimise safety and efficacy of virtual rehabilitation programmes. [23]

There are risks associated with exercise. Some patients may experience symptoms such as shortness of breath, light-headedness, chest pain, drop in blood pressure or heart rate after exercise, heart rhythm problems and muscular and joint problems.

To mitigate this risk:

- All participants with any contraindication to exercise will be excluded
- Patients will be assessed to ensure that they are suitable to follow an unsupervised home exercise programme

**Definitions**

**Adverse Event (AE):**

Adverse events are defined as **any** new medical occurrence or worsening of a pre-existing medical condition in a participant who is taking part in the trial. The AE does not necessarily have to have a causal relationship to the intervention.

**Serious Adverse Event (SAE):**

"Serious" means an adverse event resulting in:

1. Death
2. In-patient hospitalisation or prolonged hospitalisation

NOTE: Defined as an inpatient admission, regardless of the length of stay. Hospitalisation for pre-existing conditions or additional elective hospitalisation do not constitute an SAE

3. Life-threatening illness or injury

NOTE: The term "life-threatening" in the definition of "serious" refers to an event in which the participant was at risk of death at the time of the event; it does not refer to an event which hypothetically might have caused death if it were more severe.

4. Persistent or significant disability or incapacity
5. Other serious events that may jeopardize the participant and may require medical or surgical intervention to prevent one of the other five listed outcomes

*Other events that may not result in death, are not life threatening, or do not require hospitalisation, may be considered a serious adverse event when, based upon appropriate medical judgement, the event may jeopardise the participant and may require medical or surgical intervention to prevent one of the outcomes listed above

To ensure no confusion or misunderstanding of the difference between the terms "serious" and "severe", which are not synonymous, the following note of clarification is provided: The term "severe" is often used to describe the intensity (severity) of a specific event (as in mild, moderate, or severe myocardial infarction); the event itself, however, may be of relatively minor medical significance (such as severe headache). This is not the same as "serious," which is based on participant/event outcome or action criteria usually associated with events that pose a threat to a participant's life or functioning. Seriousness (not severity) serves as a guide for defining regulatory reporting obligations.

**Recording Adverse Events**

Any AEs occurring will be recorded on the electronic Case Report Form (eCRF).
The following information will be recorded: Name of AE, (event term) date of onset and end date, severity, assessment of relatedness to rehabilitation (regardless of which programme they are on), expectedness (for related AEs), and whether or not it is serious with the reason for being serious given.

**Expected adverse events during cardiac rehabilitation**

The CI, or an appropriately trained designee, should assess expectedness. This list is based on current clinical knowledge of expected AEs/SAEs for participants having cardiac rehabilitation.

- Muscle aches and pains
- Muscular injury
- Joint pain
- Light-headedness
- Vasovagal episode
- Shortness of breath
- Fatigue

- Patients wearing accelerometers may experience discomfort around the wear site and rashes in some cases.

**Anticipated adverse events following cardiac surgery**

- Wound infections
- Pain
- Atrial fibrillation
- Sleeping problems

In addition, the CI or designee must use clinical judgement to assess if an AE/SAE that is not present in this list is expected or not.
Expectedness is not required for AEs/SAEs unrelated to cardiac rehabilitation.

**Severity**

Each AE must be assessed for severity, by an appropriately trained and delegated investigator. The CI, or an appropriately trained designee, should assess severity using the following criteria:

| Severity | Description |
|---|---|
| **Mild** | An event easily tolerated by the participant, causing minimal discomfort and not interfering with everyday activities |
| **Moderate** | An event sufficiently discomforting to interfere with normal everyday activities |
| **Severe** | An event that prevents normal everyday activities |

**Relatedness**

For participants in the interventional arm, the relationship between the intervention (home-based cardiac rehabilitation) and the occurrence of each AE must be assessed and categorized by the Chief Investigator (or delegate). Related events are those that are related to the home-based exercise programme intervention.

| Unrelated | The event is not considered to be related to rehabilitation |
|---|---|
| **Unlikely to be related** | The event is considered unlikely to be related to the rehabilitation |
| **Possibly related*** | Although the relationship to the rehabilitation, cannot be ruled out, the nature of the event, the underlying disease, concomitant medications or temporal relationship make other explanations plausible. |
| **Probably related*** | The temporal relationship and an absence of a more likely explanation suggest that rehabilitation, are the most likely cause. |
| **Definitely related*** | The known effects of the rehabilitation, indicate this to be the most likely cause. |

*Adverse events that are considered to be related, probably related or possibly related to the intervention will be followed up until resolution or the event is considered stable.

**Reporting SAEs**

*For SAEs categorised as related and unexpected, a form will be completed and submitted to the sponsor within 24 hours.*

SAEs that are categorised as related to the trial intervention and unexpected will undergo expedited reporting to the Research Ethics Committee within 15 working days unless the participant has died, in which case it should be 7 days. The research team will use the NHS HRA Non-CTIMP Safety Report to REC form to report these SAEs.

These SAEs will have seriousness, relatedness and expectedness (where applicable) determined by the CI or a medically qualified delegate.

**Pregnancy reporting**

Participants who become pregnant after randomisation must stop rehabilitation as soon as the research team are aware of the pregnancy. The pregnancy must be recorded in the eCRF as a reason for withdrawal. Patients can still take part in the qualitative elements and their data can be used up until the point that they stopped rehabilitation.

**Reporting of Serious Incidents (SI)**

The event must also be assessed by the CI to determine whether it constitutes a serious incident (SI).

This is defined as an event or incident that resulted in unexpected or avoidable death, or serious harm, to one or more participants, staff, visitors or members of the public. If the event has been classed as (or is suspected to be) a SI, the Director of Quality and Effectiveness will be informed via the Clinical Governance and Risk Department (CGARD), as soon as possible by telephone. This is detailed in the trusts 'Serious Incident Reporting and Management Policy'.

**Statistical Considerations (Phase I and II)**

**Description of Statistical Methods**

The analysis and reporting of this trial will be led by a medical statistician. This will follow CONSORT guidelines (23). The number of participants screened, eligible, consenting, and randomised will be summarised, with reasons for non-participation given where possible. Baseline data will be summarised (by the randomised group in Phase II). Continuous measures will be summarised using descriptive statistics (n, mean, standard deviation, median, minimum and maximum) while categorical data will be reported as frequencies and percentages.

**The Number of Participants**

| Phase | Number of participants |
|---|---|
| **Phase I** | Minimum 15 |
| **Phase II** | 70 (35 in each arm) |

In phase II, a sample size of 70 will allow us to estimate the standard deviation of continuous outcomes including the 6MWT. [20]

**Randomisation (Phase II only)**

Eligible participants will be randomised on a 1:1 ratio to either the intervention arm (home-based exercise programme) or the control arm (standard care only) to reduce the risks of selection bias. There is no blinding for this trial. Randomisations will be performed by delegated and trained members of the research team at the James Cook University Hospital. The randomisation system will account for the diagnosis (surgery and myocardial infarction).

**Data (Phase I and II)**

**Data collection tools**

Data will be collected in accordance with written informed consent and according to General Data Protection Regulation (GDPR) guidelines. An electronic database will be used to report all trial data. Source data will be collected in the following formats:

- Baseline height, weight, medical history, date of birth/age, sex, frailty and demographics – captured in medical notes, including any other relevant data
- 6MWT – recorded in a trial-specific proforma
- Activity monitoring – Data stored in a secure web portal (anonymised)
- EQ5D5L, SF36, Barthel index– captured in the questionnaire
- SUS and MUAQ (usability scores) – are captured in questionnaires
- Frailty score – captured in questionnaire
- Participant satisfaction – captured in the questionnaire
- Adherence to intervention – captured in accelerometer wear data
- Surgical and post-PCI data – captured in medical notes
- Post-operative complications – captured in medical notes
- Outcome data and discharge details - captured in medical notes Recruitment data – captured in an electronic screening log (excel worksheet)
- Withdrawals – captured in trial-specific withdrawal forms
- Adverse events – captured in medical notes

**Data handling**

Source data will be transcribed into Case Report Forms in an electronic database by trained personnel who are on the trial delegation log. These data will be stored on secure and encrypted servers that are external to the ACU, Durham University and South Tees NHS

Hospitals Trust. The ACU core team will have password-controlled access to these data at all times to enable trial oversight. As this is a single-centre trial, the research team will also have password-controlled access to all individual CRFs.

Anonymous accelerometer raw data files will be securely stored online and will be transferred securely to the statistics team for analysis. Physical activity data will be transferred to the online server on a daily basis or more regularly to inform exercise prescription by the AI algorithm. Files will be linked to the database by unique participant identifier only. Data will be transferred at a minimum of two-time points; in phase II, this is expected to be at; 1) 50% of the way through recruitment and 2) at the end when accelerometery data collection is complete. There may be instances where a participant's GP needs to be contacted as part of the follow up process if the research team are not able to contact the participant. In this instance information regarding the participant may need to be securely transferred from the GP surgery to The South Tees NHS Hospitals Trust.

The only personally identifiable information that will leave the NHS Trust is the participants' sex and age. These data will be stored in the electronic database.

**Accelerometer data processing**

The accelerometer data will be processed by the Actigraph company, who are providing the accelerometers. We will be provided with data in the form of step count, calorie count, moderate to vigorous physical activity, light physical activity, sedentary time and sleep time.

**Information Governance**

The information collected as part of this trial will be stored securely both electronically (database and data downloads) and on paper (participant medical records, case report forms and questionnaires) and kept confidential. Data will be used according to the provision of GDPR, and any applicable regulations, and individuals will not be identifiable through any reports or publications that result from the trial.

Participants will be assigned a unique trial number at consent. All paper trial files and documents, including personal data and each participant's consent form will be retained at The James Cook University Hospital in a locked office prior to secure archiving at the end of the trial. Electronic trial records such as the screening log will be kept on secure NHS servers with access restricted to the trial team, these will be securely archived at the end of the

project. Research data and anonymised screening logs will be shared with Durham University (where the statistician is based) for analysis in collaboration with the study team.

Downloaded data will be stored on secure servers at JCUH where it will be archived and held for 5 years at the end of the trial. These data will be accessible to the clinical research team as well as the ACU. An auditor may access data as required. Data collected in the trial will be used to support other research and teaching in the future and may be shared anonymously with other researchers.

The data stored electronically in the database will contain age/date of birth, sex and assigned trial number for each participant, but no other personally identifiable data.
Participants who withdraw from the trial will have all data collected up until the point of withdrawal included in the trial, except where withdrawal is due to a trial related AE. In this event, the participant will be followed until a stable outcome is achieved. Where a participant who has withdrawn agrees, data to answer the primary endpoint of the trial can be collected and analysed.

**Retention of Personal Data**

Personal data will be needed to enable follow up of participants and to disseminate details of the trial and trial findings to participants. This data will be held on local files by the research team.

**Archiving**

Study data will be held securely by the South Tees NHS Hospitals Trust in accordance with their local policies for a period of 5 years after the last visit from the last participant. The Trust has access to a research archiving service (RESTORE).

**Quality control and assurance (Phase I and II)**

**Risk Assessment**

We will carry out a risk assessment of this trial and will continue to review the level of risk. The risk to the participants will be explained in the PIS.

**Trial Registration**

This trial will be registered with ISRCTN.

**Site Initiation and Training**

The Initiation visit will be performed by the Chief Investigator and Principal Investigator once approval from the HRA and REC have been granted. This may go ahead prior to confirmation of capability and capacity from South Tees Research & Development (R&D) if necessary, but recruitment would not start until after all approvals are in place.
Specific training will be given to research staff on use of the randomisation system, and eCRF system and what constitutes source data. The research team and the rehabilitation team may be specifically trained to perform the 6MWT and Frailty score if training is required.

**Monitoring**

The trial will be monitored by the PI to ensure that it is conducted in line with the protocol. In addition, the trial may be evaluated by an auditor or government inspector, who will also be allowed access to all case report forms, source documents, trial files and trial facilities.

**Internal Audits**

The R&D team may perform internal audits of the trial. As such, any part of the RECAP trial may be inspected at any time to ensure the trial is being conducted according to the principles of the International Council for Harmonisation (ICH) Good Clinical Practice (GCP) and GDPR.

**Serious Breaches**

A serious breach will be reported to the Sponsor and to the ethics committee as soon as it is identified. Serious breaches are defined as a breach of the protocol, which is likely to affect to a significant degree the safety or physical or mental health of a trial participant or the scientific value of the trial.

**Protocol Compliance**

It is the responsibility of the CI to ensure that the clinical trial is run in accordance with the protocol. This task may be delegated to a suitably qualified or experienced member of the research team, but the CI will retain overall responsibility.

Protocol deviations, non-compliances and breaches are departures from the approved protocol. Deviations from the protocol occur in clinical studies and the majority of these events are technical deviations that are not serious breaches. These events should be documented on the deviation tracking log. The CI and PI will review the deviation tracking log at intervals throughout the trial.

Unintentional protocol deviations will be documented and reported to the CI and sponsor. Where necessary, Corrective and Preventative Actions (CAPA) will be implemented. These will also be documented and reported to the CI and sponsor.
Deviations found to recurring frequently are not acceptable and could be classified as a serious breach.

**Ethics (Phase I and II)**

**Good Clinical Practice**

The trial will be run according to the principles of ICH GCP, and in accordance with relevant UK legislation and the protocol.

**Approvals**

The trial will not start until a favourable opinion has been given by an NHS REC and the HRA. In addition, governance approval must be confirmed by the South Tees Hospitals NHS Trust R&D Offices prior to starting recruitment.

**Funding**

This trial is currently funded by the South Tees NHS Trust.

**Insurance**

NHS Indemnity is in place to cover all aspects of clinical treatment and care provided as part of this trial.

**Study governance (Phase I and II)**

**Study Sponsor**

South Tees Hospitals NHS Foundation Trust is the trial Sponsor.

**Amendments**

The CI will liaise with the HRA and REC (if needed) to determine if an amendment is substantial or not and trial procedures will not be changed without the mutual agreement of the CI, Sponsor and the PI.

Substantial amendments will be submitted to the REC and will not be implemented until this approval is in place. It is the responsibility of the PI to submit substantial amendments.

Non-substantial amendments may be made at any time with a record of the amendment held in the Trial Master File. Any non-substantial amendment that requires an update to the trial documentation will be submitted to the NHS REC for acknowledgement of the revised version of the document.

Substantial amendments and those minor amendments which may impact the site will be submitted to the relevant NHS R&D Departments for notification to determine if the amendment affects the NHS permission for the site. Amendment documentation will be provided the PI.

**Patient remuneration**

Patients will not be paid for participation.

Appendix

## Amendment log

| Date | Amendment | Document | Amendment Description | Updated Document | Comments |
|---|---|---|---|---|---|
| 06/12/2022 | Amendment 2 | Protocol | Changed exclusion criteria to reflect the fact that we can recruit patients who are already on other trials as long as it doesn't affect outcomes and (2) added clarification on what "Social circumstances" include. | Protocol Version 2.0 Dated 7th November 2022 | |
| 02/05/2023 | NSA001 | Protocol | To update patient numbers to 17 from 20 for phase 1 | Protocol Version 2.0 Dated 2nd May 2023 | Note, protocol version number (2.0) wasn't updated in this Amendment. This was later updated in a subsequent amendment.<br><br>Change to Phase 1 sample size wasn't also updated in all places throughout the protocol. |

Appendix

| | | | | | |
|---|---|---|---|---|---|
| 31/05/2023 | Amendment 4 | Protocol | Updated Qualitative data collection method for staff from structured interviews to Focus Group and/or structured interviews. Updated location of sessions, to the "hospital and/or conducted via telephone or online virtual meeting platforms".<br><br>Updated conduct method of patient structured interviews to "Patient interviews may also be conducted during their final visit.", in addition to via "telephone".<br><br>Updated Phase I sample size to a "minimum of 15" to help collect all necessary data. (Last amendment NSA001 only updated the sample size from 20 to 17 in one section of the protocol)<br><br>Updated the protocol to say we may ask for consent by post or digital means. | Protocol Version 2.1<br><br>Dated 31st May 2023 | |

Appendix

| | | | | | |
|---|---|---|---|---|---|
| 03/07/2023 | Amendment 5 | Protocol | The research protocol no longer states the patients will be contacted every two weeks by a health care professional. They will only be contacted if there are any concerns that need addressing. Minor font changes and also added an amendment log at the end of the protocol. | Protocol Version 2.2 Dated 03rd July 2023 | |

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## 10. Appendix

Screenshots from the App. The app may be updated, and the screens may look different.

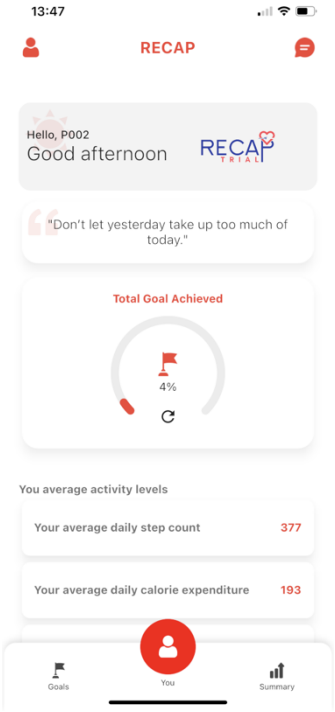



*Figure 1 Welcome Screen showing percentage of goals achieved*

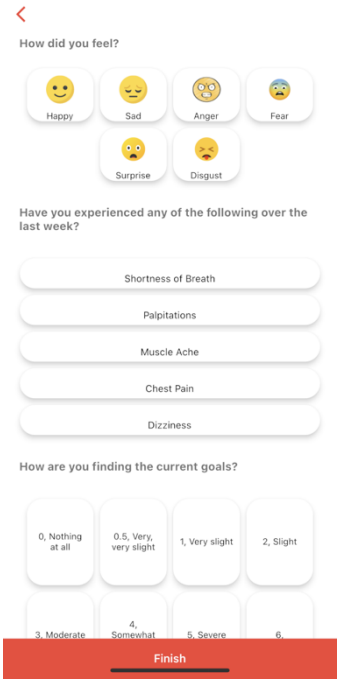



*Figure 2 Welcome Screen – user can select how they are feeling*

Appendix

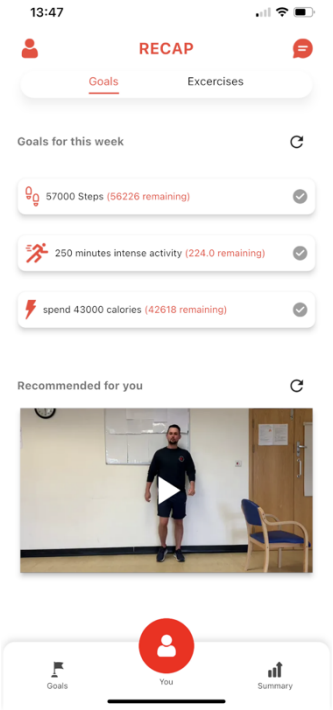



*Figure 3* Goals Screen of the App




*Figure 4* Summary Screen of the App

# Appendix E RECAP Trial Consent Form

## CONSENT FORM

| | |
|---|---|
| IRAS ID: | 315483 |
| Study Title:<br>[Study Number:] | **R**ehabilitation through **E**xercise prescription for **C**ardiac patients using an **A**rtificial Intelligence-based **P**rogramme - **RECAP** |
| Study Doctor: | Dr Pasan Witharana,<br>James Cook University Hospital, Marton road, Middlesbrough, TS43BW 01642850850 |
| Study Sponsor & Data Controller: | The Sponsor funds the study and is the data controller |
| Participant ID: | |

**Please INITIAL the box where you agree.**

1. I confirm that I have read the information sheet dated _____ (version ____) for phase ___ of the above trial. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily. ☐

2. I understand that my participation is voluntary and that I am free to withdraw at any time without giving any reason, without my medical care or legal rights being affected. ☐

3. I understand that relevant sections of my medical notes and data collected during the study may be looked at by individuals from the regulatory authorities or from the NHS Trust, where it is relevant to my taking part in ☐

this research. I give permission for these individuals to have access to my records.

4. I understand that anonymised information about me relevant to the trial will be held on a secure database, which is hosted on an external server and will be transferred to individuals within the research team, including members at Durham University, for analysis. All data will be anonymised using a participant identification number and stored securely on restricted servers for a period of 5 years after the end of the trial. Any publications resulting from this trial will not include any personal identifiable information. ☐

5. I understand that anonymised information about me that is collected via the accelerometers and the mobile app will be held on an online database. All data will be anonymised using a participant identification number. At the end of the study, this data will be transferred and stored securely on restricted servers for a period of 5 years after the end of the trial. Any publications resulting from this trial will not include any personal identifiable information. ☐

6. I understand that the information collected about me will be used to support other research and teaching in the future, and may be shared anonymously with other researchers ☐

7. I agree to my General Practitioner being informed of my participation in the trial, including any necessary exchange of information about me between my GP and the research team. ☐

8. I understand that if I lose the capacity to decide about my healthcare changes during the trial, I will not be asked to undertake any further trial activity, however routinely collected information relevant to the trial may be collected. ☐

9. I agree to take part in the above trial. ☐

**Optional: leave the boxes below (10a and 10b) blank if you do not wish to take part in the optional interviews**

10a. I understand that I may be invited to take part in an interview about my experiences of taking part in the trial. I am willing to be contacted about this. ☐

10b. I am happy for my contact details to be forwarded securely to the interviewers. ☐

| Name of Participant | Date | Signature |
|---|---|---|
| Name of Person taking consent | Date | Signature |

# Appendix F Participant Information Sheet

**Rehabilitation through Exercise prescription for Cardiac patients using an Artificial Intelligence based Programme – RECAP**

**Phase II**

**Why am I receiving this information sheet?**

We have given you this information leaflet because we would like you to consider taking part in a research we are conducting at your hospital. Taking part in the trial is entirely up to you. Before you decide if you want to join, it is important that you understand why the research is being done and what it would mean for you.

Please take time to read through the following information. Discuss it with friends and relatives if you wish, and please ask us if there is anything that is not clear or if you would like more information.

You are free to decide whether or not to take part in this trial. If you choose not to take part, this will not affect any future care you will receive. If you decide to join the study and later change your mind, you will be able to stop at any time without giving a reason.

If you think you might like to take part, please wear comfortable footwear to your clinic appointments as you will be asked to perform walking tests.

**Why are we doing this research trial?**

Cardiac rehabilitation helps patients improve their physical activity levels after surgery and heart attacks. It has been shown to reduce hospital readmission rates and reduce the risk of death in the long term.

Traditionally cardiac rehabilitation has been offered via classroom-based sessions. However, attending hospital-based sessions may not be practical for some patients due to the availability of transport and the risk of infection. If we can move the rehabilitation classes

from the hospital to the home, it will make it more accessible for patients. This small clinical trial will help us work out if it is practical to carry out a larger clinical trial to determine the effectiveness of a home rehabilitation programme. It may also help us understand if home rehabilitation can be as good as hospital rehabilitation and if we can use technology to help achieve successful home rehabilitation.

We have created a mobile app that can be installed on your phone. We will use accelerometers to track your physical activity. These are devices that look like a watch, which you will wear on your wrist. Information about the physical activity levels will be transmitted wirelessly from the accelerometer to the app. Through the app, you can then view your activity levels. You will also be given weekly goals in three domains (step count, calorie expenditure and the number of minutes spent in moderate to vigorous physical activity). The goals will be adapted to you based on your own physical activity levels.
If you decide not to take part in the home rehabilitation programme, you can still attend the hospital-based cardiac rehabilitation sessions.

**What are we doing?**

We are carrying out a research trial to see whether a home-based cardiac rehabilitation programme is practical or not. As part of this trial, we will assess how usable the technology is. We will also look at the impact of this exercise programme on your quality of life and fitness levels.
We are recruiting 70 patients to participate in this trial. The entire programme is 8 weeks long.

**What happens next?** The rehabilitation team will speak to you about the trial when you next visit the hospital or during the next phone consultation. You will have the opportunity to find out more about the trial and ask any questions you may have. We will also confirm that you are eligible to participate in this trial. A member of the research team will talk you through the information sheet and ensure that you understand all the information given here.
What would taking part involve?

**Initial Visit**

If you decide to participate in the study, you will be asked to sign a consent form, and with your consent, we will send a letter to your GP to inform them that you are taking part in this trial. You will then be asked to complete some questionnaires about your general health and your quality of life. You will undergo an assessment of your fitness which will consist of a walking test.

You will be randomly allocated to the hospital-based exercise group or the home-exercise group.

At the initial visit, if you have been allocated to the home exercise group, we will give you an accelerometer (this is a device that looks like a watch you can wear on your wrist) and a charging dock for it. We will also guide you on downloading two apps on your phone.

We will then show you how to use the accelerometer devices and the apps and answer any questions you may have.

**During the exercise programme**

If you've been allocated to the hospital-based exercise group, you will attend the James Cook University Hospital once a week for 8 weeks and participate in group exercise classes (please see exercise class booklet).

If you've been allocated to the home exercise group, you will be asked to wear the accelerometer throughout the day. It will track your activity levels, including your step count, calorie expenditure, the number of minutes you spent doing moderate to intense exercise, sedentary time, and sleep time. During your initial visit, we will set your physical activity goals for the first week.

You will automatically get a new set of goals at the beginning of every week via the app. The rehabilitation team at the hospital will continue to review these goals to make sure they are appropriate for you.

**Final visit**

At the final visit, we will ask you to complete the questionnaires you completed at the initial visit and additional questionnaires which will ask about your experience with the programme. We will also repeat the walking test. If you were given an accelerometer, you would be required to return this at the final visit. You will also not be able to use the app after the programme has ended.

Please be aware that the research team or the sponsor may withdraw you from the study for scientific or safety reasons at any time.

**What else might be involved if I take part? (Optional)**

As part of the trial, we would like to find out about your views and experiences of the study. The interviews will be recorded (audio only), and the audio recordings will be securely held in a hospital database. The recordings will be held for 12 months, and within this time, they will be transcribed. All person identifiable information will be redacted in the transcriptions. This is separate from the main trial, so you do not have to agree to be interviewed. If you are interested, we will obtain your consent to take part and ask your permission to securely share your contact details so a member of the research team can get in touch with you to discuss this further.
Please note that these interviews are optional, and you do not have to participate.

**What are the benefits of taking part?**

We know that cardiac rehabilitation offers various benefits to patients. Previous studies looking at home-based rehabilitation programmes have found that they are effective in increasing the physical activity of patients. However, we do not know if a fully automated rehabilitation programme will result in better patient recovery but that is what we expect this trial to tell us.

If you are allocated to the home exercise programme, a healthcare professional (HCP) will monitor your progress through the programme remotely. This will allow us to see how active you have been on a day-to-day basis. If we feel that something doesn't look right, we will get in touch with you to make sure that you are doing well.

The results of this trial will be used to inform the design of a bigger trial and it may benefit the future care of patients.

**What are the potential risks of taking part?**

In a hospital-based exercise class, you would be guided by a physiotherapist. However, in the home-based programme, you wouldn't have any face-to-face sessions as part of RECAP. This may mean, that if you were to experience any problems during your home exercise sessions, you may not have access to help immediately. There are some common side effects of exercise, which include muscle injury, joint pain and stiffness. If you experience any symptoms during your exercises, please call us on the number given at the end of this information sheet.

Breach of data held online is another possibility. However, we have taken steps to minimise the risk of this.

**What steps will be taken to minimise any potential risks?**

Only patients who are deemed eligible for the trial by their clinician will be able to take part. All patients will be assessed on their fitness and ability by a specialist heart nurse/physiotherapist. We will continually review your progress through the programme and if we find any of the goals that have been set for you is unrealistic or not safe, we will modify them. These changes will be reflected in your app.
In addition to this, we will contact you if we have any concerns.
We have minimised the risk of a data breach by adding extra security to the online database. This means anyone who is not registered on the mobile app will not be able to access the data. Even those who are registered will only be able to access the data that are relevant to them. We have also ensured that no person identifiable data is stored online.

**Will I be paid to take part?**

No, taking part in the trial is voluntary and you will not be paid for your time. We have designed the trial so that wherever possible, the visits you need to make to the hospital coincide with those you would normally have as part of your standard care. If the appointments do not coincide with routine appointments, travel expenses will not be paid.

What will happen if I don't want to carry on with the trial?

Your decision to take part in this research is voluntary, you can change your mind at any stage and this will not affect the care you receive. If you decide to withdraw from the trial, we will keep and continue to use all your previously collected data and you will not be asked to perform any more assessments or attend any trial visits.

If you decide to withdraw, we will ask if you consent for us to collect routine data from your medical records without the need for you to be contacted by the trial team or attend any more trial visits. This is entirely optional and will not affect your ongoing care.

**Who is organising and funding this trial?**

This research is sponsored by South Tees NHS Hospital Trust. The research team includes members from the James Cook University Hospital, Durham, and the Imperial College London.

**Will taking part in the research be confidential?**

The South Tees Hospitals NHS Foundation Trust is the sponsor for this trial. We will be using information from you and your medical records in order to undertake this trial and will act as the data controller for this trial. This means that we are responsible for looking after your information and using it properly.

Your rights to access, change, or move your information is limited, as we need to manage your information in specific ways for the research to be reliable and accurate. If you withdraw from the study, we will keep the information about you that we have already obtained. To safeguard your rights, we will use the minimum personally-identifiable information possible. Your data will be assigned a unique identification number, and this will be used to collate and analyse your data. You will not be identified by name outside of the hospital. Information collected about you will be used to support other research in the future and may be shared with other researchers.

You can find out more about how we use your information at https://understandingpatientdata.org.uk/what-you-need-know and stees.researchdevelopment@nhs.net and by visiting https://www.hra.nhs.uk/planning-and-improving-research/policies-standards-legislation/data-protection-and-information-governance/gdpr-guidance/templates/template-wording-for-generic-information-document/.

The hospital will use your name, NHS number and contact details to:

- Contact you about the research trial
- Ensure that relevant information about the trial is recorded in your medical notes
- To oversee the quality of the trial

Individuals from the South Tees Hospitals may look at your medical and research records to check the accuracy of the research trial. The people who analyse the information will not be able to identify you and will not be able to find out your name, NHS number or contact details. The Trust will keep identifiable information about you for 5 years after the trial has finished.
Information and data collected during your participation may be used to support other research and teaching in the future and might help in the development of other clinical trials.

**Where will this information be stored?**

Data from this trial will be stored by the clinical research team at the hospital in secure offices and will be kept on paper in your medical records and a trial file. The data collected from the app and the accelerometers will be held on an online database provided by Google. No person-identifiable data will be stored in this database. The data collected by the accelerometers will also be transmitted to the study team based at the hospital. We will use extra security to enhance the security of this database. We will use another secure database to store study data. Only authorised persons involved with running the trial will have access to this. The data will be downloaded from the database and stored on secure servers; these data will be shared with members of the research team who are involved in their analysis. The data will be kept for the duration of the trial (until the last patient completes their 12-week follow-up) and for 5 years after the trial finishes in accordance with data protection legislation.

**Who has reviewed this trial?**
All research in the NHS is looked at by an independent group of people, called a Research Ethics Committee, to protect your interests. This clinical trial has been reviewed by the Berkshire Research Ethics Committee.

**What if I have a complaint?**

In the event that something goes wrong and you are harmed during the research due to someone's negligence, then you may have grounds for a legal action for compensation against the South Tees Hospitals NHS Foundation Trust but you may have to pay your legal costs.

If you are unhappy or have any concerns about any aspect of the trial and wish to complain formally and confidentially, you can do so through the NHS complaints procedure. To discuss your concerns or make a complaint you can contact a member of the PALS (Patient Advise and Liaison Service) on 0800 0282451, or on 01642 854807 / 01642 282657
0800 0320 202 or by visiting stees.pals@nhs.net

**For further information**

If you have any questions or concerns regarding the trial please contact:

Cardiac Research Team:

The RECAP Trial,

Research Department

James Cook Hospital

Tel: 01642 854321 / 01642 282410

Monday to Friday 9:00 till 16:00

p.witharana@nhs.net

**Thank you for taking the time to read this information.**

1 copy for patient, 1 copy into notes

# Appendix G Staff Focus Group Topic Guides

**RECAP Staff Focus Group Topic Guide**

**Session Outline**

**Welcome**

- Introduction
- Outline the aims and objectives of the session
- Is there anything we could do to help improve your participation in this focus group?
- Any initial questions?

**Ground rules**

- **Confidentiality** – Everything that is discussed to stay within the group. However, we cannot guarantee participants will respect this confidentiality.
- You would not be able to withdraw what was discussed after the session
- Sessions will be recorded. Only audio files will be used for transcription and data will be **anonymised** before analysis
- Please raise any concerns you wish to raise in confidence, in person after the group
- Your views and ideas discussed during the session will not affect your role in the programme going forward or any future work
- All feedback is valued, and discussion is encouraged
- Please raise your hand if you wish to say something and respect each other's views
- Informal session and a safe space for discussion

**Introductions**

- Please introduce yourself including your role in the programme
- *Distribute individual feedback forms for participants to complete before the session starts (see below)

Appendix

**Warm-up / Ice breaker**

- In 3 words describe how you felt delivering the sessions

**Topic Guide**

**Introduction**

- What motivated you to help with the delivery of the sessions?

**Guiding Questions**

- How would you describe your overall experience with the study?
- What did you think the delivery of the programme would be like?
- What was it actually like?
- When patients were first informed about the study, were they interested in taking part?
- How do you think home-based rehabilitation compares with hospital-based rehabilitation?
- Did you feel the regular phone calls helped the patients?
- What was your experience with the web portal?
- What was it like reviewing the goals that were set by the algorithm?
- Did you feel well supported in your role during the programme?
- If you have delivered rehabilitation sessions in the past, how was the delivery of a home-based programme different?
    - Were the participants more or less motivated?
    - What did you feel motivated them to take part and do better?

- Did you identify any barriers for the participants to taking part in the programme?
- Did you feel the allocated time for you to help with the delivery was sufficient?

- What did you think went well with the delivery of the programme and the study in general?
- What did you think could be done differently or improved?
- Would you offer this programme to patients in the future?
- Is there anything else that you would like to discuss?
- Follow up questions

**Short Questions**

- Name 3 things that were good about the study
- Name 3 things that could have been different
- What was the most significant moment in the study for you? This could be positive or negative

**Conclusion**

- Thank you for attending the focus group. It has been very useful.
- All the points discussed including any comments will be anonymised during the analysis
- If there is anything you'd like to discuss in person, please contact the chief investigator

# Appendix H Patient Interview Topic Guide

## Outline

### Welcome

- Introduction
- Outline aims and objectives of the interview
- Any initial questions?

### Ground rules

- **Confidentiality** – Everything we discuss is confidential
- You would not be able to withdraw what was discussed after the interview
- Interview will be recorded. Audio files will be used for transcription and data will be **anonymised** before analysis
- Please let us know about any concerns you may have
- All feedback is valued
- Interview is expected to take less than 30 minutes

### Warm up / Ice breaker

In 3 words describe how you felt taking part in the programme

## Topic Guide

### Introduction

- What motivated you to take part in the programme?

### Guiding Questions

- How would you describe your overall experience with the study?
- What did you think the programme would be like?
- What was it actually like?
- How familiar were you with the concept of home rehabilitation?

- How did you find the goals that were prescribed to you?
- What was your experience with the app?
- What was it like wearing the accelerometer?
- What motivated you to do well in the programme?
- What did you think about the motivational quotes in the app?
- What other features would you have liked to see in the app?
- What are your thoughts on the phone calls from the rehabilitation team?
- What did you think could be done differently or improved?
- Would you recommend this programme to others?
- Is there anything else that you would like to discuss?
- Follow up questions

## Short Questions

- Name 3 good things about the programme
- Name 3 things that could have been different

## Conclusion

- Thank you for taking part in the interview. It has been very useful.
- All the points discussed including any comments will be anonymised during analysis
- If there is anything else you'd like to discuss, please let us know.

# Appendix I Phase II Feasibility RCT: Regression Analysis Tables

*Table 9.1 Analysis of EQ5D5L Utility Scores*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | 0.004 | -0.002, 0.010 | 0.15 |
| Sex | | | |
| Male | — | Reference | |
| Female | -0.024 | -0.151, 0.102 | 0.70 |
| Time | | | |
| Initial | — | Reference | |
| Followup | -0.008 | -0.061, 0.045 | 0.75 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | 0.057 | -0.013, 0.126 | 0.11 |

[1]CI = Confidence Interval

*Table 9.2 Analysis of EQ5D5L VAS*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | 0.231 | -0.267, 0.730 | 0.36 |
| Sex | | | |
| Male | — | Reference | |
| Female | -5.74 | -16.3, 4.85 | 0.28 |
| Time | | | |

Appendix

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Initial | — | Reference | |
| Followup | 0.051 | -5.09, 5.19 | 0.98 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | 8.12 | 1.43, 14.8 | 0.018 |

[1]CI = Confidence Interval

*Table 9.3 Analysis of SF-36 Physical Functioning*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | -0.053 | -0.734, 0.628 | 0.88 |
| Sex | | | |
| Male | — | Reference | |
| Female | 10.1 | -4.33, 24.5 | 0.17 |
| Time | | | |
| Initial | — | Reference | |
| Followup | 1.68 | -3.10, 6.46 | 0.48 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | -10.6 | -16.9, -4.19 | 0.002 |

[1]CI = Confidence Interval

*Table 9.4 Analysis of SF-36 Role Physical*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | 0.803 | -0.431, 2.04 | 0.20 |

Appendix

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Sex | | | |
| Male | — | Reference | |
| Female | -13.0 | -38.9, 13.0 | 0.32 |
| Time | | | |
| Initial | — | Reference | |
| Followup | 5.71 | -8.40, 19.8 | 0.42 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | 36.9 | 18.6, 55.1 | <0.001 |

[1]CI = Confidence Interval

*Table 9.5 Analysis of SF-36 Role Emotional*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | 1.05 | 0.016, 2.07 | 0.047 |
| Sex | | | |
| Male | — | Reference | |
| Female | 0.882 | -20.8, 22.6 | 0.94 |
| Time | | | |
| Initial | — | Reference | |
| Followup | -3.77 | -13.5, 5.93 | 0.44 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | 20.6 | 7.87, 33.4 | 0.002 |

[1]CI = Confidence Interval

*Table 9.6 Analysis of SF-36 Vitality*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | 0.918 | 0.299, 1.54 | 0.004 |
| Sex | | | |
| Male | — | Reference | |
| Female | -4.76 | -17.8, 8.25 | 0.47 |
| Time | | | |
| Initial | — | Reference | |
| Followup | -0.251 | -7.67, 7.16 | 0.95 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | 9.77 | 0.221, 19.3 | 0.045 |

[1]CI = Confidence Interval

*Table 9.7 Analysis of SF-36 Mental Health*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | 0.882 | 0.351, 1.41 | 0.002 |
| Sex | | | |
| Male | — | Reference | |
| Female | -2.72 | -13.9, 8.49 | 0.63 |
| Time | | | |
| Initial | — | Reference | |
| Followup | -2.13 | -6.19, 1.93 | 0.30 |
| Time:treatment | | | |

Appendix

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| 0 | — | Reference | |
| 1 | 8.79 | 3.39, 14.2 | 0.002 |

[1]CI = Confidence Interval

*Table 9.8 Analysis of SF-36 Social Functioning*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | 0.865 | 0.107, 1.62 | 0.026 |
| Sex | | | |
| Male | — | Reference | |
| Female | 3.09 | -12.9, 19.1 | 0.70 |
| Time | | | |
| Initial | — | Reference | |
| Followup | -1.71 | -9.46, 6.04 | 0.66 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | 20.3 | 10.1, 30.4 | <0.001 |

[1]CI = Confidence Interval

*Table 9.9 Analysis of SF-36 Bodily Pain*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | 0.499 | -0.258, 1.26 | 0.19 |
| Sex | | | |
| Male | — | Reference | |
| Female | -9.96 | -25.9, 6.00 | 0.22 |

Appendix

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Time | | | |
| Initial | — | Reference | |
| Followup | 2.14 | -5.18, 9.46 | 0.56 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | 10.8 | 1.23, 20.4 | 0.028 |

[1]CI = Confidence Interval

*Table 9.10 Analysis of SF-36 General Health*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | 0.226 | -0.227, 0.679 | 0.32 |
| Sex | | | |
| Male | — | Reference | |
| Female | -5.87 | -15.4, 3.70 | 0.22 |
| Time | | | |
| Initial | — | Reference | |
| Followup | -2.86 | -6.64, 0.915 | 0.13 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | 1.32 | -3.68, 6.33 | 0.60 |

[1]CI = Confidence Interval

*Table 9.11 Analysis of SF-36 PCS*

Appendix

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | -0.096 | -0.157, -0.035 | 0.003 |
| Sex | | | |
| Male | — | Reference | |
| Female | 0.174 | -1.12, 1.47 | 0.79 |
| Time | | | |
| Initial | — | Reference | |
| Followup | 0.393 | -0.107, 0.893 | 0.12 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | -0.869 | -1.53, -0.207 | 0.011 |

[1]CI = Confidence Interval

*Table 9.12 Analysis of SF-36 MCS*

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|
| Age | 0.268 | 0.107, 0.428 | 0.002 |
| Sex | | | |
| Male | — | Reference | |
| Female | -0.746 | -4.14, 2.64 | 0.66 |
| Time | | | |
| Initial | — | Reference | |
| Followup | -0.655 | -1.82, 0.509 | 0.26 |
| Time:treatment | | | |
| 0 | — | Reference | |
| 1 | 2.86 | 1.31, 4.41 | <0.001 |

Appendix

| Characteristic | Beta | 95% CI[1] | p-value |
|---|---|---|---|

[1]CI = Confidence Interval

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