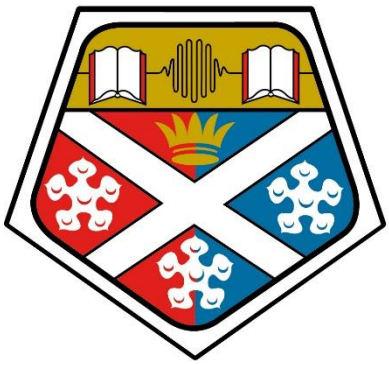

University of Strathclyde Glasgow

Co-Design and Development of a Dosage and Intensity Monitor (DAIM) for Stroke Rehabilitation

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This thesis is submitted in fulfilment of the requirements for the degree of PhD in Biomedical Engineering

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Declaration

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed: 

Date 30/07/2025

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Abstract

Rehabilitation is essential for regaining motor, cognitive, and functional abilities following stroke. Recent updates to the National Clinical Guidelines for Stroke in the UK and Ireland now recommend a minimum of three hours of daily multidisciplinary therapy, a fourfold increase from the previous 45-minutes. Accurately measuring the true delivery of rehabilitation dosage and intensity, however, remains a critical challenge. Commonly, clinical trials describe their control groups as "standard physiotherapy," but fail to detail accurately what this entails. Without accurate measurement techniques, it is impossible to ensure guideline adherence, correctly interpret research outcomes, or meaningfully compare new interventions against existing practices.

This thesis presents the co-design, development, and evaluation of a Dosage and Intensity Monitor (DAIM), a digital system specifically created to objectively quantify rehabilitation dosage and intensity in stroke survivors across home, research, and clinical environments. Built through a user-centred design framework aligned with Medical Research Council (MRC) guidance for complex interventions, the thesis employed focus groups, iterative prototyping, stakeholder feedback, and survey-based validation to ensure the system was relevant, usable, and grounded in real-world rehabilitation needs.

The final DAIM system integrates a wearable movement sensor and NFC tagging with a user-friendly mobile application, accurately capturing rehabilitation activities such as walking, cycling and sit-to-stand. Real-time feedback, gamified goal setting, and group-based progress tracking were embedded to promote motivation, engagement, and adherence to rehabilitation. Software prototypes, developed through collaborative design methods and Android Studio prototyping, ensured optimal accessibility and usability, particularly for users with stroke-related cognitive or motor impairments.

Validation testing in both clinical and research settings demonstrated that the DAIM provided highly accurate (96% agreement with optical tracking) data with a user friendly system (100% user success) that agreed (1.23 min difference, on average) with clinician-recorded data. This system, therefore, addresses the critical gap in objectively measuring rehabilitation dosage and intensity, offering a robust solution for both clinical practice and research applications. Future work should focus on optimising hardware ergonomics, producing a market ready system and scaling up usability testing.

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Publications Arising from this Work

Poster Presentations

Boyd, F., Slachetka, M., & Kerr, A. The codesign of a community self-rehabilitative intervention to support stroke rehabilitation: a focus group. *BioMedEng 2023,* September 2023, Swansea, UK.

Boyd, F., Slachetka, M., & Kerr, A. The codesign of a community self-rehabilitative intervention to support stroke rehabilitation. *UK Stroke Forum 2023,* December 2023, Birmingham, UK.

Boyd, F., Slachetka, M., Sweeney, G., & Kerr, A. Novel wearable intensity tracker for stroke rehabilitation: feasibility study. *UK Stroke Forum 2024,* December 2024, Liverpool, UK.

Oral Presentations

Boyd, F., Slachetka, M., Dunlop, M., & Kerr, A. Feasibility and Agreement of a Wearable Intensity Tracker for Lower-Limb Stroke Rehabilitation. *BioMedEng 2024,* September 2024, London, UK.

Boyd, F., Slachetka, M., Sweeney, G., & Kerr, A. Novel wearable intensity tracker for stroke rehabilitation: feasibility study. *UK Stroke Forum 2024,* December 2024, Liverpool, UK.

1st Author of Thesis Publications

Boyd, F., Sweeney, G., Barber, M., Forrest, E., Dunlop, M., & Kerr, A. (2025). Co-Designed Digital Device for Tracking Rehabilitation Dosage in a Clinical Environment After Stroke: Mixed Methods Validity and Feasibility Study. *JMIR Rehabil Assist Technol*, *12*, e68129. https://doi.org/10.2196/68129

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Kerr, A., Grealy, M., Slachetka, M., Wodu, C. O., Sweeney, G., Boyd, F., Colville, D., & Rowe, P. (2024). A Participatory Model for Cocreating Accessible Rehabilitation Technology for Stroke Survivors: User-Centered Design Approach. *JMIR Rehabilitation and Assistive Technologies*, *11*, e57227-e57227. https://doi.org/10.2196/57227

Sweeney, G., Boyd, F., Keogh, M., Lyczba, P., Forrest, E., Rowe, P., Barber, M., & Kerr, A. (2025). A technology-enriched approach to increasing rehabilitation dose after stroke: Clinical feasibility study. *Clin Rehabil*, *39*(6), 740-749. https://doi.org/10.1177/02692155251333542

List of Abbreviations

BLE	Bluetooth Low Energy
CCRT	Co-Creation of Rehabilitation Technology
CHSS	Chest Heart and Stroke Scotland
DAIM	Dosage and Intensity Monitor
IMI	Intrinsic Motivation Inventory
IMUs	Inertial Measurement Units
IoT	Internet of Things
mHealth	Mobile Health
MRC	Medical Research Council
NHS	National Health Service
PIS	Participant Information Sheet
RCT	Randomised Control Trial
SSNAP	Sentinel Stroke National Audit Programme
SUS	System Usability Scale
TERG	Technology-Enriched Rehabilitation Gym
UCD	User-Centred Design
UEQ	User Experience Questionnaire
UI	User Interface
UX	User Experience

Chapter 1. Introduction

This chapter is an introduction to the PhD thesis. It will present the context and importance of the work and the general structure of the thesis.

1.1. Background

A stroke, or cerebrovascular accident (CVA), occurs when the blood supply to part of the brain is interrupted or significantly reduced, preventing brain tissue from receiving essential oxygen and nutrients (Sacco et al., 2013). This can result from a blockage (ischaemic stroke) or bleeding (haemorrhagic stroke) in the brain (Amarenco et al., 2009). Common symptoms include sudden numbness or weakness in the face, arm, or leg, confusion, trouble speaking or understanding speech, visual disturbances, dizziness, loss of balance, and severe headache (Murphy & Werring, 2020). Each year, there are about 100,000 strokes in the UK, with 1.3 million stroke survivors living across the UK (NICE prevalence of stroke, 2023). Strokes are the fourth leading cause of death and the single largest cause of complex disability in the UK (NHS England - North West, 2024). It is crucial to act quickly when symptoms of a stroke appear, as immediate treatment can significantly improve outcomes and reduce the risk of long-term disability (NHS Inform, 2025).

The number of people being admitted to hospital following a stroke has risen by 28% in the last 20 years (NHS England, 2024). There has also been a noticeable increase in strokes amongst younger adults, particularly those under 55, which has been linked to lifestyle factors including rising obesity rates (Scott et al., 2022).

Long-term projections of stroke in the UK are worrying. Between 2015-2035, the incidence of stoke is expected to rise by 60% per year, while prevalence is projected to increase by 120%, this could lead to societal costs that could triple the current figure of £26 billion (King et al.,

2020). Several factors contribute to this trend including an aging population, advances in treatment that have improved survival outcomes and thus increased the number of stroke survivors, and escalating obesity rates that may offset earlier reductions in stroke incidence (Boehme et al., 2017).

Mortality rates from acute stroke have also declined, largely due to improvements in acute care and early intervention strategies (Seminog et al., 2019). Consequently, more people are surviving their stroke and living with long-term disabilities (Yu & Kapral, 2019). Among these, the most common and recognised deficit is motor impairment (Langhorne et al., 2009). Motor impairment can be defined as a loss or limitation of muscle control or movement, or a limited mobility (Langhorne et al., 2009). Current general recommendations to alleviate or restore lower-limb motor function centre on high-intensity, repetitive, task-specific rehabilitation, an approach also supported by stroke clinical guidelines (NICE guideline [NG236], 2023). For many stroke survivors, regaining the ability to walk independently or with minimal assistance is identified as their highest rehabilitation priority, as walking is foundational for performing essential daily activities, engaging socially, and maintaining independence (Rudberg et al., 2021). Research consistently demonstrates that targeted and intensive lower-limb rehabilitation leads to meaningful improvements in balance, gait velocity, endurance, and overall functional mobility, reinforcing its importance within stroke recovery programmes (Langhorne et al., 2009).

Rehabilitation after stroke is crucial for optimal recovery, aiming to restore as much independence as possible and ultimately a good quality of life (Li et al., 2024). Reflecting mounting evidence, the updated National Clinical Guideline for Stroke for the UK and Ireland has increased its recommended therapy, moving from the 2016 the 2016 call for “an accumulative 45 minutes of each appropriate therapy every day” to a new 2023 standard of a “minimum of 3 hours of multidisciplinary therapy a day… at least 5 days out of 7”

(Intercollegiate Stroke Working Party, 2016, 2023). This expanded approach encompasses physiotherapy, occupational therapy, and speech and language therapy, all tailored to meet individual needs and maximise recovery outcomes (Mahase, 2023; Tang et al., 2024).

Despite these strengthened guidelines, evidence suggests that even the previous targets were not consistently met, with research finding the average amount of therapy per day of stay was significantly below the recommended 45 minutes for each relevant therapy (Gittins et al., 2020). This shortfall was attributed to highly varied nurse and therapy staffing levels exacerbated by understaffing issues, and organisational factors from the type of stroke team, timely therapy assessments, and the presence of weekend therapy services. Additionally, less than half of stroke teams provided an extended weekend therapy service.

In addition to this, stroke rehabilitation progress is still largely measured through manual tracking, typically based on therapists' notes or infrequent assessments. The Sentinel Stroke National Audit Programme (SSNAP) database is a national stroke register that audits care from approximately 250 stroke teams in England, Wales, and Northern Ireland via a combination of electronic data entry by the stroke team and manual recording into the SSNAP's online clinical database (SSNAP Therapy factsheet, 2024). Whilst SSNAP captures daily therapy duration and other key metrics, it lacks data on the structure, content, and timing of therapy sessions, and inconsistencies in therapist-reported durations have been noted with a tendency to overestimate the duration of treatment sessions (Gittins et al., 2020).

Accurate measurement is critical to ensure guidelines for rehabilitation intensity and dosage are being met, particularly given the recent guideline updates recommending increased rehabilitation time. Without precise tracking methods, it becomes challenging to evaluate current practice, support personalised care, or rigorously assess new rehabilitation interventions (Chang, 2022). Robust measurement systems are also essential for driving

research, facilitating the development of innovative approaches, and ensuring that rehabilitation strategies are evidence-based and effective (Stockley et al., 2024). Therefore, the absence of standardised, automated and objective methods for monitoring rehabilitation dosage and intensity hinders adherence to guidelines, personalised care, and research into innovative interventions.

In response to the shortfall of meeting rehabilitation targets, it has been recommended to increase the number of qualified therapists and support workers, as well as reorganising and expanding therapy services; however changes would have likely required a substantial rise in funding and resources (Gittins et al., 2020). Without such investment available, it remains unclear how services can now meet a fourfold rise in therapy provision. Consequently, technology-based interventions such as digital rehabilitation platforms, and telerehabilitation are being explored alongside conventional therapy extend reach, optimise existing resources, and provide stroke survivors with the intensified rehabilitation they need.

Technology-supported interventions, including digital rehabilitation platforms and telerehabilitation, are increasingly utilised in stroke rehabilitation to enhance patient engagement and optimise therapy outcomes (Chen et al., 2021; Laver et al., 2017). Integrated sensors and software have the potential to monitor the intensity and dosage of rehabilitative interventions, helping users take personal responsibility to meet their rehabilitation targets and enabling healthcare providers to make real-time adjustments to the users' plan. Research suggests personalised, tracked therapy can significantly enhance motor function and overall recovery (Chen et al., 2015; Laver et al., 2017).

Therefore, this project specifically targets high-intensity lower-limb rehabilitation as the optimal starting point for quantifying rehabilitation dosage and intensity. This aligns strategically with the evolving stroke rehabilitation guidelines, which increasingly emphasise

accurately monitoring dosage and intensity to optimise rehabilitation outcomes. The ambition of this thesis is to develop and validate an innovative and accessible solution for measuring and managing rehabilitative tasks among stroke survivors. The specific objectives of this research will be detailed at the conclusion of the subsequent literature review chapter, following a comprehensive analysis of current practices, identified gaps, and user-focused design requirements.

1.2. Research Questions and Aims

The research questions for this PhD thesis are:

1. What are the existing methods for measuring rehabilitation 'dosage' and 'intensity', and what gaps or limitations exist in these approaches?
2. How can the perspectives of stakeholders be incorporated into the design of a dosage and intensity monitoring system to improve its relevance, usability, and acceptability?
3. To what extent can a newly developed technological system provide an accurate and comprehensive picture of a person's rehabilitation activity across home, research, and clinical settings?
4. Can gamifying the monitoring of dosage and intensity enhance user engagement, and motivation during rehabilitation?

The aims of this PhD thesis are to:

1. To identify and review current methods for measuring rehabilitation 'dosage' and 'intensity,' and to highlight key gaps or limitations that warrant the development of new technological solutions.
2. To gather stakeholder perspectives via a co-design process, thereby establishing the design and engineering requirements for a dosage and intensity monitoring system.

3. To establish and validate a standardised technological method for accurately measuring the ‘dosage’ and ‘intensity’ of rehabilitative tasks.
4. To co-design, develop and evaluate a dosage and intensity monitoring system that can accurately capture rehabilitation ‘dosage’, and the ‘intensity’ of lower-limb rehabilitation activities.
5. To co-create and evaluate a mobile application with co-operative gamification elements that can provide a real-time feedback system of dosage and intensity data captured across home, research and clinical settings, and enhance user motivation throughout the rehabilitation journey.

1.3. Overview of the PhD Studies

This thesis follows the Medical Research Council (MRC) Framework, used for the development and evaluation of complex health interventions (Skivington et al., 2021). The four stages of this framework are as follows:

1. Development of the intervention
2. Piloting and feasibility
3. Evaluation
4. Implementation

Chapter 2 and Chapter 3 address stage 1 of the MRC framework. Chapter 2 contains four main sections covering key subject areas underpinning this thesis, including:

- Defining Rehabilitation
- Measuring Rehabilitation
- Telerehabilitation
- Measuring Human Movement

Chapter 3 describes the co-design process used to achieve a user-centred design approach for developing a dosage and intensity monitoring system with an accompanying mobile application. It also introduces the design framework that guides the thesis.

Chapters 4-7 align with Stages 2 and 3 of the MRC frameworks, where key components of the system are developed, validated, and then piloted in both research and clinical settings. Chapter 4 focuses on the 'dosage' component, covering hardware and software development, feasibility, accuracy studies, and pilot and clinical trials. Chapter 5 centres on the 'intensity' component of the system, including feasibility and accuracy testing with chronic and acute stroke survivors. Chapter 6 details the mobile application development, including design principles, gamification mechanics to support stroke rehabilitation, prototype development, system integration testing, and stakeholder feedback. Chapter 7 outlines a final pilot study evaluating the acceptability of the prototype DAIM.

Chapters 8 and 9 align with the fourth stage of the MRC framework, where results of the final study are discussed within the context of existing literature and current research. While Chapter 9 concludes the thesis by offering overall recommendations for future research and highlighting the key contributions of these studies to the field.

Chapter 2. Literature Review

This chapter reviews the literature surrounding stroke rehabilitation, examining current approaches and technologies used to measure rehabilitation dosage and intensity. It is structured into five sections, beginning broadly and progressively becoming more specific: 1) methodology, 2) a short introduction to stroke rehabilitation, 3) measuring stroke rehabilitation, 4) telerehabilitation and 5) measuring human movement. The primary aim of this review was to synthesise evidence on how stroke rehabilitation dosage and intensity are quantified in both clinical and research settings. Clarifying these parameters will inform the subsequent development of a technology solution, later refined through a co-design focus group.

This review addresses the question: *What existing technologies and methods (subjective or objective) are used to measure rehabilitation dosage and intensity across physical, cognitive, and speech rehabilitation contexts, and what are the key gaps or limitations identified within these approaches?*

The chapter concludes by summarising how the literature review informed the overall research thinking, aims, and objectives guiding the remainder of this project.

2.1. Methods

This literature review was conducted as a narrative review, with the aim of synthesising and critically interpreting existing evidence on how rehabilitation dosage and intensity are measured in stroke rehabilitation across physical, cognitive, and speech domains. A narrative approach was selected to allow integration of diverse study designs, technologies, and conceptual perspectives, which would not be well suited to a narrowly defined systematic review.

To ensure the review was conducted in a thorough and transparent manner, the search and synthesis process was informed by established guidance on conducting structured literature reviews in information systems and eHealth research (Levy & Ellis, 2006; Paré & Kitsiou, 2017). Paré and Kitsiou, 2017 define eHealth as the use of information and communication technology (ICT)-based systems, services, and resources to facilitate health management (e.g., telehealth or telemedicine) (Paré & Kitsiou, 2017).

2.1.1. Search Strategy

The search was conducted in December 2024 across multiple databases including: PubMed (MEDLINE), Cochrane Library, IEEE Xplore, ACM Digital Library, and Google Scholar. Additionally, manual searches of reference lists from relevant articles were undertaken to identify further potentially eligible sources.

Search terms were developed iteratively based on the research question and refined through preliminary scoping searches. Keywords and free-text terms were grouped around five key concepts: rehabilitation domain, dosage, intensity, measurement methods and technologies, and stroke-related conditions (Table I). Database-specific adaptations of the search strategy were used where appropriate.

Table 1 Topic groups and keywords used in the searches

Topic Group	**Keywords**
Rehabilitation	Physical OR Physiotherapy OR "Physical therapy" OR "Exercise therapy" OR Cognitive OR "Cognitive rehabilitation" OR "Cognitive therapy" OR Speech OR "Speech-language therapy" OR "Speech rehabilitation" OR "Speech therapy"
Dosage	Dosage OR Dose OR "Rehabilitation dosage" OR "Treatment dosage" OR Volume OR Amount OR Frequency OR Duration OR "Exercise prescription"

Intensity	Intensity OR "Rehabilitation intensity" OR "Treatment intensity" OR "Exercise intensity" OR Effort OR Exertion
Measurement / Methods / Technologies	Measure* OR Track* OR Monitor* OR Assess* OR Evaluation OR "Mobile application" OR Wearable OR "Assistive technology*" OR Device OR "Sensor-based" OR Tele* OR "Self-report*" OR Questionnaire* OR Diary OR Physical Activiy*
Condition (Stroke)	Stroke OR "Cerebrovascular Accident" OR CVA OR "Brain infarction"
Note. "*" means free text	

2.1.2. Criteria

Studies were selected based on predefined inclusion and exclusion criteria to ensure relevance to the review aims. Eligible studies included peer-reviewed journal articles, conference papers, and relevant grey literature that described methods for measuring or monitoring rehabilitation dosage or intensity in adult stroke populations. Studies across physical, cognitive, and speech rehabilitation contexts were included, as were studies employing subjective (e.g. self-report, diaries) or objective (e.g. wearable sensors, digital tracking) measurement approaches. Only publications written in English were considered, with no restrictions placed on publication date.

Following the literature search and relevance screening, a broad body of literature was identified and synthesised to inform this review.

2.2. A Short Exploration into Stroke & Stroke Rehabilitation

2.2.1. Recognising and Diagnosing Stroke: Clinical Features and Symptoms

2.2.1.1. Impact on Lower Limbs: Mobility Challenges

While stroke can affect all motor output the focus of this review is restricted to the lower limbs, as this has a major impact on mobility and is a priority during the early stages of recovery. This restriction also allows the development of an appropriate system within a three year time frame. Stroke can significantly impact the lower limbs, causing impaired function and reduced participation in daily living activities (Langhorne et al., 2009). Common clinical features affecting the lower limbs include hemiparesis, or hemiplegia, which results in weakness or paralysis on one side of the body, typically contralateral to the site of the brain lesion. This impairment affects a stroke survivor's ability to walk, balance, and perform coordinated movements (Jørgensen et al., 2010).

The degree of lower limb dysfunction can vary depending on the severity of the stroke. Studies have shown that about 65% of stroke survivors have trouble walking immediately following a stroke, and nearly half of them continue to have significant mobility issues six months post-stroke (Hendricks et al., 2002; Wade & Hewer, 1987). Specific issues in the lower limbs include spasticity, which is an increase in muscle tone leading to stiffness and resistance to movement. This can result in abnormal gait patterns, such as foot drop, circumduction (swinging the leg outward), and decreased ability to bear weight on the affected side (Ada et al., 2006). Sensory deficits, such as reduced proprioception and tactile sensation, also contribute to challenges in balance and coordination, further complicating mobility and increasing the risk of falls (Tyson et al., 2006). Rehabilitation efforts focus on improving strength, balance, and coordination through targeted physical therapy and exercise programmes. Despite these efforts, it is reported

that around 30% of stroke survivors are still unable to walk independently six months post-stroke (Teasell et al., 2020).

2.2.1.2. Communication

Aphasia is a language disorder that affects the ability to communicate, commonly resulting from damage to the language-dominant hemisphere of the brain, usually the left hemisphere. Aphasia can impair speech, comprehension, reading, and writing skills. It affects about one-third of stroke survivors and can significantly impact their quality of life and social interactions (Brady et al., 2016). Brady et al., 2016, conducted a comprehensive Cochrane review evaluating the effectiveness of speech and language therapy for aphasia. The review included 57 trials with over 3000 participants, concluding that speech and language therapy significantly improves functional communication, receptive language, and expressive language abilities compared to no therapy. Another key study by Breitenstein et al., 2017, investigated the effectiveness of intensive speech and language therapy in chronic aphasia patients (Breitenstein et al., 2017). This randomised controlled trial involved 158 participants and demonstrated that intensive speech and language therapy led to significant improvements in language skills compared to conventional therapy. The study highlighted the importance of intensive and task-specific language interventions in enhancing recovery in aphasia. Additionally, a study by Bhogal et al., 2003 examined the dose-response relationship in aphasia therapy, finding that more intensive therapy over shorter periods resulted in better outcomes, reinforcing the value of concentrated therapeutic efforts (Bhogal et al., 2003).

2.2.2. Stroke Rehabilitation Definition

Stroke rehabilitation is a comprehensive programme of therapies designed to help individuals recover skills lost after a stroke, focusing on improving movement, speech, and daily living activities (Dworzynski et al., 2015). It involves various therapies, including physical,

occupational, and speech therapy, to help patients regain lost abilities and adapt to life after stroke. The goal is to maximise independence and improve quality of life (Dworzynski et al., 2015).

Stroke rehabilitation typically follows a cyclical problem-solving process: (1) assessment to identify and quantify the patient's needs; (2) goal setting to define realistic and attainable goals for improvement; (3) intervention to assist in achieving these goals; and (4) reassessment to evaluate progress against the agreed goals (Dworzynski et al., 2015; Langhorne et al., 2011).

Stroke rehabilitation is a collaborative process delivered by a coordinated multidisciplinary team of allied health professionals (AHP) including doctors, nurses, physiotherapists, occupational therapists (OT), speech and language therapists (SLT), clinical psychologists, and social workers (National Clinical Guideline Centre (UK), 2013). These AHPs coordinate their work through regular meetings to produce patient-centred care, a recommended approach involving a partnership where both the AHP and person with stroke bring important information and the AHP views the person in the context of their lives and help them not only to acquire the skills to handle the immediate issues influencing their health but to also learn strategies and link with community resources that promote, protect, and improve their health over the long term (Bartels et al., 2016; Wolf & Baum, 2011). Stroke rehabilitation is a collaborative process delivered by a coordinated multidisciplinary team of allied health professionals (AHP) including doctors, nurses, physiotherapists, occupational therapists (OT), speech and language therapists (SLT), clinical psychologists, and social workers (National Clinical Guideline Centre (UK), 2013). These AHPs coordinate their work through regular meetings to produce patient-centred care, a recommended approach involving a partnership where both the AHP and person with stroke bring important information and the AHP views the person in the context of their lives and help them not only to acquire the skills to handle the immediate issues influencing their health but to also learn strategies and link with

community resources that promote, protect, and improve their health over the long term (Bartels et al., 2016; Wolf & Baum, 2011).

Rehabilitation should begin as soon as possible after a stroke and recovery can continue for months or years after stroke (Langhorne et al., 2011). 2023 NICE guidelines (section 4.1) state that "people with stroke should be considered to have the potential to benefit from rehabilitation at any point after their stroke" (NICE guideline [NG236], 2023). This indicates that if someone presents with functional deficiencies years after a stroke, they are still entitled to and encouraged to actively partake in rehabilitation. NICE guidelines also recommend that individuals receive at least three hours of total multi-disciplinary therapy, five days a week, delivered across different stages of the stroke pathway, from acute hospitals to community and home-based settings (NICE guideline [NG236], 2023).

2.2.3. Does Physical Rehabilitation Work?

A 2025 Cochrane review of 267 trials (~21,800 people) aimed to determine whether physical rehabilitation approaches are effective in the recovery of function and mobility in people with stroke and if one physical rehabilitation approach is more effective than another in both chronic and acute cases. They found that organised physical rehabilitation significantly improves peoples' ability to perform daily activities, leg strength/mobility, balance, and walking capacity compared to no rehabilitation (Todhunter-Brown et al., 2025). Todhunter-Brown et al., 2025 found that immediate improvements in independence during activities of daily living (ADL) were substantial, with a large standardised mean difference (SMD) (SMD = 1.32, 95% CI 1.08 to 1.56, Z=10.81, $p < 0.00001$) across 52 studies involving 5403 participants; these gains remained significant over the long term (SMD = 0.52, 95% CI 0.17 to 0.88, Z = 2.88, p = 0.004). Similarly, immediate gains in motor function were significant (SMD = 1.01, 95% CI

0.80 to 1.22, Z = 10.81, p < 0.00001) and sustained at long-term follow-up (SMD = 0.50, 95% CI 0.22 to 0.78, Z=3.48, p=0.0005). Immediate improvements in balance, measured via the Berg Balance Scale, were notable (MD=4.54, 95% CI 1.36 to 7.72); however, these were not maintained in the long term (MD=0.58, 95% CI -1.71 to 2.87, Z = 0.50, p = 0.62). Gait velocity also improved modestly immediately following rehabilitation (SMD=0.23, 95% CI 0.05 to 0.42, Z = 2.80, p = 0.005), but this benefit similarly was not sustained long-term (SMD=0.01, 95% CI -0.18 to 0.20, Z=0.22, p=0.82).

This lack of long-term sustainability for both gait velocity and balance, however, was a methodological issue (Todhunter-Brown et al., 2025). The author highlighted that the primary reason for uncertainty regarding the long-term maintenance of balance and gait velocity improvements is the scarcity of follow-up data, rather than a confirmed loss of these gains over time. This lack of sufficient longitudinal data makes it challenging to draw definitive conclusions about the sustainability of observed benefits. Therefore, the lack of sustained long-term effects should be interpreted as an indication of insufficient evidence rather than conclusive proof that improvements in gait velocity and balance diminish over time.

Table 2 expands upon this by identifying recent reviews that have examined the effectiveness of different subcategories of physical rehabilitation. These include not only general physical therapy but also occupational therapy and robotic-assisted interventions, among others.

Table 2 Summary of Stroke Rehabilitation Interventions: Effectiveness, Key Evidence, and Statistical Outcomes

Intervention	Effectiveness	Key Evidence	Key Stats	Limitations
Physical Therapy (Todhunter-Brown et al., 2025)	Improves ADLs, mobility, balance	Cochrane review of 267 trials	Physical rehabilitation was more effective than no physical rehabilitation for immediate outcome (SMD* 1.32, 95% CI 1.08 to 1.56; $I^2 = 93\%$).	No clear superiority among methods; long-term data limited
Occupational Therapy (Vásquez-Carrasco et al., 2025)	Improves ADLs, cognitive function	Meta-analysis: 12 RCTs	SMD = 2.47; 95% CI = 0.24 to 4.70; $I^2 = 100\%$; p=0.03	Varied evidence across domains
Robotic-Assisted Therapy (Mehrholz et al., 2020)	Improves motor function, strength when combined with usual care	Cochrane review (45 trials); RATULS trial	When combined with (odds ratio) 2.01, 95% CI 1.51 to 2.69; p < 0.00001	No superiority over intensive therapy; cost
Task-Oriented Training (French et al., 2016)	Improves walking, STS, arm function	Cochrane review (32 trials)	Walking distance MD 34.80, 95% CI 18.19 to 51.41	Heterogeneous effects; unclear optimal dose
Virtual Reality (Laver et al., 2025)	Improves balance when used in combination with usual care	Cochrane review (12 trials)	SMD 0.68, 95% CI 0.46 to 0.91; $I^2 = 13\%$	No clear benefit for gait; tech variability
Telerehabilitation (Alayat et al., 2022)	Improves balance and functional mobility	Meta-analysis of 13 trials	Balance (SMD 0.33 [95% CI 0.03 to 0.63]; p=0.03) Functional mobility (SMD 0.27 [95% CI 0.02 to 0.52]; p=0.03)	Dependent on access and engagement
**SMD = Standardised mean difference*				

2.2.3.1. Measurement Criteria

In light of the breadth of rehabilitation strategies, this thesis will focus on the quantitative measurement of three fundamental mobility tasks, walking, cycling, and sit-to-stand (STS), as core indicators of rehabilitation progress. These tasks were chosen because they represent essential domains of functional recovery and collectively capture improvements in strength, balance, and endurance. Walking ability is arguably the most critical outcome for stroke survivors, as independent gait is closely tied to personal autonomy and quality of life. Even modest gains in gait speed or walking distance can translate to significantly better community participation, and many rehabilitation trials use walking metrics as primary endpoints (Mehrholz et al., 2020). Being able to walk independently (with or without aids) is also a key goal reported by patients and is associated with reduced dependency in ADLs.

Cycling, while not an ADL itself, provides a controlled means to build bilateral lower-limb coordination and aerobic capacity. Importantly, the cyclical motion of leg cycling shares biomechanical and rhythmical similarities with walking, meaning improvements gained through cycling training can carry over to gait function (Barbosa et al., 2015). Cycling is a safe, scalable task that stroke patients can perform even from a seated position, making it an excellent indicator of lower-limb work capacity and a proxy for aerobic fitness improvements.

Finally, the STS movement is one of the most fundamental transitional tasks in daily life as it is required for getting out of a chair, bed, or toilet. STS performance is one of the most affected functional tasks after stroke and is key to independent living, as an inability to stand up independently confines a person to seated positions (Sánchez-Martínez et al., 2024). Therefore, regaining a strong, balanced STS is therefore a primary goal in rehab and a clear measure of functional lower-extremity strength. By tracking STS (e.g. the time or repetitions a patient can perform), therapists gauge improvements in leg power, balance, and confidence.

2.2.4. Self-rehabilitation

Self-rehabilitation is defined as a "tailored therapy program where for most of the time, the patient performs rehabilitation exercises independently to the presence of a clinician" (Everard et al., 2021). Self-rehabilitation programmes can occur in a variety of settings, such as a hospital, rehabilitation centre, physical therapy office, or at home. Examples of technologically assisted self-rehabilitation include rehabilitation apps (PCs and Tablets), robots, non-immersive virtual reality systems, and functional electrical stimulation machines. Examples of non-technologically assisted self-rehabilitation include balance and walking programmes, bimanual exercises, functional reaching and grasping tasks, and unsupervised constraint-induced movement therapy (Everard et al., 2021).

Self-rehabilitation is recognised and recommended by the UK and Ireland guidelines (NICE guideline [NG236], 2023), but is also recognised internationally (Rahman et al., 2023). The guidelines recognise that stroke survivors often require assistance with daily tasks after hospital discharge and may require this assistance for many years or permanently, self-rehabilitation is an important part of addressing these long-term needs and maximising functional capacity, symptom management, cognitive skills, daily activities, minimising future chances of stroke, improve communication, and social involvement. Additionally, self-rehabilitation allows the person to have a sense of control throughout their stroke recovery journey (Szczepańska-Gieracha & Mazurek, 2020).

Self-rehabilitation programmes and conventional therapy have been shown to be equally effective for improving motor function and activity after stroke. Everard et al, 2021, conducted a meta-analysis of 35 randomised controlled trials involving 2,225 participants, finding no significant difference between the two interventions. Specifically, for motor function, the Standardised Mean Difference (SMD) was .09, with a 95% Confidence Interval (CI) of −.11 to

.28 and a p-value of .39, while for activity outcomes, the SMD was .08, with a 95% CI of −.04 to .19 and a p-value of .18. Despite these findings suggesting statistical equivalence, the low SMDs (both under .1) reflect very small effect sizes, indicating minimal practical significance. The confidence intervals for both outcomes included zero, raising concerns about the reliability of the results. Moreover, the evidence for motor function was rated as low due to moderate heterogeneity ($I^2 = 40\%$), suggesting variability across studies, while the evidence for activity outcomes was considered moderate, with no significant heterogeneity ($I^2 = 0\%$) (Everard et al., 2021).

Self-rehabilitation programmes also have the added benefit of being cost-effective, with Llorens et al., 2015's study reporting that the in-clinic programme cost $654.72 more per person than the home-based telerehabilitation programme (Lloréns et al., 2015). A note from this study was that transportation costs to and from the clinic accounted for 87.77% of the total cost of the intervention and the VR device would require an estimated $800 for purchasing. It's important to acknowledge that the cost estimations in the study were specific to their context in Spain and didn't account for the cost of instrumentation for the in-clinic intervention and the cost of hardware for the VR device was treated as a one-time expense; considerations would need to be made when the technology required an upgrade or became obsolete.

Whittaker er al., 2024 found that self-rehabilitation programmes, often supported by healthcare professionals outside structured sessions, are low-cost and potentially improve health-related quality of life (Whittaker et al., 2024). Their meta-analysis of 43 randomised controlled trials, with data from 27 trials, indicated that self-rehabilitation programmes demonstrated a clinically significant improvement in health-related quality of life, with a mean difference of 0.03 units in the quality-of-life utility index. This effect was particularly evident when self-rehabilitation was the primary intervention, with a moderate certainty of a meaningful positive difference of 0.03 units (95% CI, 0.01-0.06). For individuals with a neurological diagnosis, the mean

difference was also 0.03 units (95% CI, 0.00-0.06), with high certainty of evidence. Even when self-rehabilitation was part of a multimodal intervention, it still showed a positive effect with a utility index mean difference of 0.02 units (95% CI, 0.01-0.03), also supported by high certainty evidence. These programmes are believed to positively influence self-efficacy and health-related quality of life through strategies like goal setting, self-monitoring, and coping mechanisms.

Whittaker did, however, find that self-rehabilitation programmes are likely to be more costly than usual care alone; but this cost increase is small, and the evidence supporting this finding is of low certainty. For instance, the meta-analysis found a mean difference in cost of £44, but with a broad confidence interval (-£63 to £149). Despite this potential for a slight cost increase, self-rehabilitation programmes were considered cost-effective also due to the significant improvements in health-related quality of life and the low cost per Quality Adjusted Life Year (QALY) gained. The Institute for Clinical and Economic Review (ICER) for stand-alone self-rehabilitation interventions was £1440, considerably lower than Australia's accepted willingness-to-pay threshold of £24000 per QALY gained (Whittaker et al., 2024).

It is theorised that self-rehabilitation programmes are as effective as conventional therapy because of the flexibility these programmes to tailor to the individuals needs which allow them to target their unique deficiencies; additionally, these programmes can be done at the person's own pace within their own home. Dorward et al., 2025, looked at this from a qualitative standpoint and found that people with stroke and their carers reported positive experiences with self-rehabilitation programmes, participants reported that their key driving factors during their self-rehabilitation were related to seeing results, achieving their goals, their overall desire for autonomy, pre-existing habits and following clinicians' instructions (Dorward et al., 2025). People however, have said that their barriers to self-rehabilitation included safety concerns, lack of direction and lack of confidence.

Poor adherence to self-rehabilitation programmes is a common problem. To address this challenge, researchers have recommended several strategies, including providing real-time sessions with a therapist, using technology to monitor patients' progress, setting clear and measurable goals, and educating patients about their condition (Everard et al., 2021).

2.2.4.1. Summary

Stroke rehabilitation is effective, particularly when delivered intensively through multidisciplinary teams. To optimise recovery, understanding the dose and intensity of interventions is crucial, as these factors directly influence outcomes. Community-based and self-rehabilitation solutions are essential to meet treatment recommendations, and self-rehabilitation has been shown to be effective and potentially cost-effective, offering a flexible, low-cost alternative to traditional therapy. To fully support recovery, it's important to measure and monitor the dose and intensity of interventions, providing individuals with clear targets and evaluating progress. By doing so, healthcare providers can ensure interventions align with recommended practices, track compliance, and improve overall rehabilitation services.

2.3. Measuring Stroke Rehabilitation

This section begins by examining the overarching UK guidelines for stroke rehabilitation services. It then transitions to a discussion of how dosage and intensity is measured in both clinical and research settings ending in definitions and objectives for this thesis.

2.3.1. Guidelines to Follow

The National Clinical Guidelines for Stroke in the UK and Ireland (Intercollegiate Stroke Working Party, 2023), were recently updated in 2023. The guidelines aim to “provide authoritative, evidence-based practice guidance to improve the quality of care delivered to

every adult who has a stroke in the United Kingdom and Ireland, regardless of age, gender, type of stroke, location, or any other feature"(Welsh Government, 2024).

The updated guidelines recommend that rehabilitation plans should be tailored to an individual's goals and preferences, with progress tracked by regularly assessing outcomes against these personalised targets. To add to this, during acute rehabilitation multidisciplinary teams should complete weekly reviews to evaluate the needs, goals, and progress of the patient. This includes treatment efficacy and planning for discharge.

Progress is measured by how well individuals apply the functional skills learned during therapy to their everyday activities. The definition of "functional skills", however, may vary between wards, leading to differences in how progress is assessed. It is important to note, however, that these guidelines do not provide explicit instructions on how to measure or track rehabilitation. In general, in the UK, meeting stroke care guidelines is monitored by the Sentinel Stroke National Audit Programme (SSNAP) and Scottish Stroke Care Audit (SSCA) for Scotland.

Participation in SSNAP is embedded in the NHS Standard Contract, making it a contractual requirement for providers of stroke services. SSNAP reports that over 90% of expected stroke hospital admissions are recorded on SSNAP by acute stroke services (SSNAP Therapy factsheet, 2024). Established in 2002 the SSCA audits all hospitals managing acute stroke care in Scotland (Scottish National Audit Programme, 2024). The audit is key to the Scottish Stroke Improvement Programme, and NHS boards use the audit to evaluate their stroke care against national standards, targets and monitor the quality of care delivered in compliance with national standards.

With these frameworks, healthcare providers understand the type of data collection they should be partaking in, and this results in their own localised data collection methods. Within both academic and clinical spheres, however, there is growing interest in interpreting these collected

outcomes as measures of "dosage" or "intensity", due to these factors directly linking to patient outcomes. By quantifying how much therapy a patient receives and with what level of difficulty or effort, clinicians and researchers can more accurately determine which approaches are most effective. Yet, the concepts of dosage and intensity remain ambiguous, leading to varied definitions and highlighting the need for a standardised approach.

2.3.2. What is “Dosage” & “Intensity”?

The definition of “dosage” in stroke rehabilitation in broad terms refers to the total amount of therapeutic intervention provided to patients, encompassing parameters such as frequency, intensity, duration, and overall volume of exercises, activities, or tasks (Lang et al., 2009; Stinear et al., 2020). At its core, dosage aims to capture how much rehabilitation is being administered, yet there is considerable variability in how these parameters are defined and measured.

There are a variety of differing measurable outcomes which are frequently used to measure dosage. Duration, measured in total minutes of therapy provided could be used, however frequency could indicate how many sessions occur each week. Other measures, such as the number of movement/task repetitions completed, can serve as indicators of therapy volume, and intensity may be inferred from the challenge level of tasks or the amount of effort required (Lang et al., 2009; Lohse et al., 2014). Exercise therapy often applies the FITT principle: frequency, intensity, time, and type, as a framework for quantifying dose (Thompson et al., 2013).

Dorsch and Elkins, 2020, have argued that dose should be quantified through the number of exercise repetitions rather than the time spent practising so that counting tangible units of work can provide a more meaningful measure of dosage (Dorsch & Elkins, 2020). Simply knowing how many minutes of therapy a patient receives or how often they attend sessions does not

reveal what actually transpires during that time. Ada et al., 2009, for instance, found that only 34% of therapy time involved task-specific practice, revealing a disconnect between the measured input (time) and the meaningful therapeutic content (task-specific repetitions) (Ada et al., 2006).

Similarly, efforts to gauge “meaningful and patient-centred activity” have proven difficult due to the subjective and individualised nature of meaningful engagement in therapy (Levy et al., 2019; Lohse et al., 2014). Moreover, intensity, which is recognised (insert reference) as crucial for promoting neuroplasticity and functional gains, is also notoriously hard to quantify (Bernhardt et al., 2019; Stinear et al., 2020).

Intensity has been referred to as the frequency of repetitions of the desired movement, amount of external work, or amount of time that is dedicated to practice (Goikoetxea-Sotelo & van Hedel, 2023). Intensity has also been equated to dosage (the number of hours spent in exercise therapy). It has also been referred to as the number of repetitions, training sessions, therapy duration, and patient activity during each of the repetitions. Goikoetxea-Sotelo and van Hedel, 2023, highlight this in their paper and provide a thorough discussion of the diverse definitions of "intensity" in neurorehabilitation, particularly focusing on motor outcomes in stroke recovery. Although the authors did not conduct a systematic review for the definitions and limited their systematic search of intensity measures to a single database (PubMed) (Goikoetxea-Sotelo & van Hedel, 2023). The paper did show there tends to be a large crossover between the definitions of intensity and dosage and recommended a standardised framework separating these definitions. They also found that intensity was measured via task and movement and perceived effort (Table 3).

Table 3 Published intensity measures collected by Goikoetxea-Sotelo & Hubertus J. A. van Hedel with their final deifnition.

Category of measures	Intensity measures stated	References
Dose- and dosage-related	Minutes per day	(Webster et al., 2021)
	Duration of session	(Chiu et al., 2020)
	Frequency per week	(Aramaki et al., 2019)
	Duration of the intervention speed	(Valentín-Gudiol et al., 2017)
	Time spent in the therapy	(Vloothuis et al., 2016)
	Mean hours delivered	(Veerbeek et al., 2017)
	Active minutes per session	
Cardiorespiratory capacity	(Absolute) heart rate	(Penna et al., 2021)
	% heart rate reserve	(Clos et al., 2021)
	% heart rate maximum / % peak heart rate	(Hornby et al., 2020)
	% VO2 maximum	(Wiener et al., 2019)
	% peak oxygen uptake	(Hasan et al., 2016)
	% heart rate predicted (e.g., based on age)	
Energy cost	Metabolic Equivalent of Task (MET)	(Lamotte et al., 2015)
		(Wiener et al., 2019)
Muscle work	% of peak power output	(Clos et al., 2021)
	Power output or rate of work	(Hornby et al., 2020)
	Load lifted	(Wiener et al., 2019)
	% of 1 repetition maximum	
	% of maximum workload	
Movement-related	Number of repetitions	(Hornby et al., 2020)
	“Repetitions” or “Movements” per minute	(Aramaki et al., 2019)
		(Doumen et al., 2023)
	Steps per rehabilitative session	(Lo et al., 2017)
	Acceleration of upper limb movements	(Veerbeek et al., 2017)

Task-related	Treadmill speed	(Chiu et al., 2020)
	Treadmill inclination	(Hornby et al., 2020)
	Walking velocity	(Wiener et al., 2019)
	Fastest possible speed (over-ground)/maximum tolerated speed	(Valentín-Gudiol et al., 2017)
	Walking as far as possible with minimal rests	(Hasan et al., 2016)
	% tolerated speed	
	Adding weights during walking	
Goikoetxea-Sotelo and van Hedel Definition	The amount of physical or mental work put forth by the patient during a particular movement or series of movements, exercise, or activity during a therapy session	This definition was adapted by the authors from one proposed by Page and colleagues of the ACRM Stroke Movement Interventions Subcommittee (Page et al., 2012)

It was recognised by Goikoetxea-Sotelo and van Hedel, that novel technologies like wearable inertial measurement units or rehabilitation therapy technologies could quantify the number of repetitions per session and thus meet intensity measures that were movement or task based.

SSNAP defines rehabilitation intensity using two key metrics: the median number of therapy minutes per day and the proportion of inpatients receiving at least 3 hours of motor therapy daily (SSNAP dataset changes, 2024). When shifting from 45-minute rehabilitation recommendations to 3-hours, this represented a marked increase in expected therapy intensity (delivery duration). SSNAP directly links this change by assessing clinical teams based on the percentage of patients achieving 3 hours of daily motor therapy and tracks median therapy minutes per day, as a method of raising the bar for clinical practice (SSNAP dataset changes, 2024). Taylor et al., 2018 conducted an ethnographic study into how intensity is audited in the UK (although only covered the Southeast of England) and found that measuring therapy time was problematic due to varied interpretations of ‘what counts’ and variation in reporting practices when comparing different hospitals data collection methods (Taylor et al., 2018).

The challenge of collecting consistent and meaningful rehabilitation data grows significantly once patients are discharged, often once they have achieved a certain level of functional independence in ADLs. At this stage, individuals progress to community, long term care, or self-rehabilitation where SSNAP and SSCA guidelines shift towards less frequent, six-monthly assessments. This reduced management results in an increase in responsibility on the stroke survivor to maintain their own rehabilitation efforts, further complicating the understanding and measurement of rehabilitation dosage and intensity beyond the clinical setting.

2.3.2.1. Thesis Definition of Dosage and Intensity

In this thesis, rehabilitation 'dosage' was defined as the cumulative amount of rehabilitative activity performed by a stroke survivor over a given period. This includes both the frequency (e.g. number of sessions) and duration (time spent in each activity) of rehabilitation-related movements such as walking, cycling, or sit-to-stand exercises. 'Intensity', in contrast, was defined as the effort level or difficulty of the activity performed, which could be inferred from metrics such as cadence (e.g. reps/min), pace (e.g. steps/min), or the degree of active engagement in task execution. This dual definition took inspiration from Goikoetxea-Sotelo & van Hedel, 2023, and allows future measurement systems to distinguish between how much rehabilitation was done (dosage) and how hard the user was working during it (intensity), providing a more nuanced and clinically meaningful representation of rehabilitative effort (Goikoetxea-Sotelo & van Hedel, 2023). These definitions guided the design and development of the DAIM system's sensing and data tracking components, ensuring that both dimensions could be accurately captured and fed back to users and clinicians for goal setting, monitoring, and motivation.

2.3.3. Standard Assessments and Measurements used in Clinical Rehabilitation

Several standardised clinical assessments are routinely used across NHS stroke services in the UK to monitor and evaluate physical recovery and motor function following a stroke. For assessing their overall health status, AHPs can use the Modified Rankin Scale (mRS) to categorise a persons' functional independence post-stroke (with 0 meaning no residual symptoms and 5 indicating severe disability) (NHS England Clinical Policy Unit, 2019; Wilson et al., 2002).

Another functional independence index that measures ADLs and mobility is the Barthel Index (BI). It consists of 10 basic ADL domains (e.g. feeding, bathing, dressing, transfers, walking) with performance in each scored and summed to a total out of 100 (Quinn et al., 2011). A score of 100 represents independence in self-care and mobility, whereas lower scores indicate increasing dependency (Liu et al., 2020). The BI is widely used in UK stroke rehabilitation due to its ease of use and excellent reliability, though it is less sensitive for detecting subtle improvements in higher-functioning people (NHS Institute for Innovation and Improvement, 2008).

Assessments that look specifically at mobility and balance include the Rivermead Mobility Index (RMI). This is a 5-item mobility scale that assess tasks ranging from bed mobility (turning in bed, sitting up) to transfers, standing balance, walking indoors/outdoors, and stairs. Each item is scored 0 or 1 (unable or able to perform), for a maximum total of 15 with higher scores reflecting better mobility independence (Antonucci et al., 2002).

Another assessment includes the Functional Ambulation Categories (FAC) which measures walking ability rating on a 6-point scale, used to gauge how much human support a patient requires to ambulate. The scale ranges from 0 which indicates nonfunctional ambulator (cannot

walk at all) up to 5 which indicates independent ambulator on all surfaces without any physical assistance.

Assessing rehabilitation in stroke is performed manually by clinicians, with all of the previously listed methods of assessment requiring pen-and-paper score forms and observational checklists. This manual approach inherently means that the accuracy, reliability, and consistency of the results depend heavily on the training, experience, and judgment of the individual assessor. Although AHPS, such as physiotherapists and occupational therapists, possess specialised clinical knowledge and training enabling them to make valid judgments about patient performance, the subjective nature of these assessments remains a limitation.

Human judgment introduces variability, as different clinicians may perceive and interpret patient performance differently, particularly in cases where assessment scales include broad descriptors or subjective performance criteria. It has been previously shown that standard clinical scales, such as the Fugl-Meyer assessment (FM) show a high degree of variability among different raters, ultimately leading to larger sample sizes being required to demonstrate the value of a particular intervention. (Fugl-Meyer et al., 1975; Glantz, 2012; Krebs et al., 2002)

Similarly, scales like the Action Research Arm Test (ARAT) have relatively wide scoring intervals, meaning noticeable but subtle improvements might not be adequately captured. For example, a person may demonstrate improved arm function by successfully moving their hand from their mouth to their forehead, a clear indicative of functional progress, but will receive the same ARAT score if they cannot place their hand on top of their head, as per the scoring criteria (Wilson et al., 2021).

Additionally, the timing and selection of assessments used are at the clinician's discretion, further contributing to potential variability. Clinicians may choose different assessments based

on their familiarity, perceived suitability for the patient, or practical constraints within clinical settings (Lees et al., 2012; McLoughlin et al., 2025). Although these decisions are informed by professional judgment, variability in assessment choice and timing can hinder standardisation across different settings or between different clinical teams.

Despite their established validity and widespread use, these manual assessments inevitably contain inherent limitations due to natural human error and differences in perception. Thus, while AHP-administered assessments provide invaluable structured benchmarks in stroke rehabilitation, their reliance on manual observation and interpretation underscores the ongoing need for complementary objective measurement tools and standardised protocols to reduce variability and improve reliability.

2.3.4. Assessments and Measurement used in Rehabilitation Research

Stroke rehabilitation research employs various methods to measure physical activity, ranging from traditional manual recording to advanced technological solutions. Manual methods include self-report diaries, clinical logs, and direct observational checklists, which are simple and inexpensive but prone to biases such as inaccurate recall and subjective interpretation (Gebruers et al., 2010; Lee et al., 2018). These questionnaires and functional tests such as ARAT and FMA gather about patients' ability to perform specific tasks, not their natural daily performances (Gebruers et al., 2010).

In contrast, wearable sensors such as pedometers, accelerometers, and inertial measurement units (IMUs) offer continuous and objective measurement, capturing detailed movement data including step counts, activity intensity, and limb kinematics (Lee et al., 2018; Maceira-Elvira et al., 2019). Additionally, physiological monitoring tools, like heart-rate monitors, indirectly estimate activity intensity by recording physiological responses (Lee et al., 2018). Optical tracking systems, including marker-based motion capture and markerless technologies (e.g.,

Microsoft Kinect or VR headset tracking), further enhance precision by accurately quantifying limb movements and joint angles without physical contact (Borzelli et al., 2025; Haas et al., 2015).

Despite the clear benefits of sensors and optical tracking for accuracy, these methods have seen limited adoption in day-to-day clinical practice (particularly within the NHS) for several practical reasons (Kerr et al., 2018). Cost is a significant barrier with many hospitals and clinics operate under tight budgets, and obtaining sufficient devices (and associated software) for all people can be expensive. Therapists have noted that the price of new technology is a primary obstacle to integrating it into rehabilitation services, followed by technology usability, and lack of available space as some of the biggest barriers (Sidarta et al., 2022).

2.3.4.1. "Usual Care"

In trials, "usual care" refers to the care that the targeted patient population would typically receive as part of normal clinical practice (Yorganci et al., 2020). It is also known by various interchangeable terms, including "treatment as usual" (TAU), "standard care," "routine care," "control case," or "standard treatment" (Paci et al., 2022).

A recurring issue in rehabilitation research is that many RCTs compare new therapies or technologies against a control labelled "usual care" or "standard physiotherapy" without clearly defining what that entails or quantifying its intensity or dosage. Systematic reviews have found that control interventions described as "usual care" are often poorly reported and highly variable between studies (Arienti et al., 2022; Paci et al., 2022). For example, a review of physiotherapy RCTs in multiple sclerosis noted that usual care controls were significantly under-described compared to experimental interventions, undermining the validity, generalisability, and interpretation of trial results ($p < 0.001$) (Paci et al., 2022). Additionally, a systematic review of stroke rehabilitation trials found that 13.6% of studies did not describe

their control treatment at all, and those that did used over 100 different “conventional therapy” programmes under the usual care label (Arienti et al., 2022). The study also found that only three studies (1.9%) out of 155 in stroke rehabilitation stated that their usual care was designed according to clinical guidelines (Arienti et al., 2022).

This lack of specification includes failing to report the dosage or intensity of standard care, making it unclear what the control group actually received. Such ambiguity leads to confusion and methodological issues, if usual care differs across settings or is delivered inconsistently, it becomes hard to interpret what the experimental intervention was truly compared against (Hariohm et al., 2017). Not only can this affect the estimated effect size and trial conclusions, but it also hinders replication of the study in clinical practice (Turner et al., 2024).

Arienti et al., 2022, suggests that there is no uniform definition of “usual care” however Yorganci et al, contrasts this by proposing that usual care should be defined using a multi-method approach embedded within the design of RCTs to characterise its context, structures, processes, and outcomes, as well as to identify similarities, embedded practices, heterogeneity, and subtle changes over time and across sites, thereby enhancing the reliability and validity of intervention effectiveness interpretations s (Arienti et al., 2022; Yorganci et al., 2020). Whilst this proposal of a usual care definition could be feasible, it doesn’t reflect what is currently happening in practise as Paci et al., 2022, found no correlation between TIDieR scores and the year of publication ($p < 0.001$), suggesting that there has been no improvement in the description of interventions over time (Paci et al., 2022).

Telerehabilitation and advanced technological methods such as wearable sensors, accelerometers, and optical tracking systems could significantly bridge this gap by providing more objective, accurate, and detailed measurements of rehabilitation activities. These technologies enable consistent, quantifiable recording of dosage, frequency, and intensity of

therapeutic interventions, reducing reliance on clinician interpretation and manual reporting. By adopting telerehabilitation platforms, clinicians and researchers can remotely monitor and analyse patient performance in real-time, promoting transparency and standardisation across studies. Ultimately, integrating these advanced tools into rehabilitation research and clinical practice could lead to clearer insights, improved methodological rigour, and a more comprehensive understanding of effective rehabilitation interventions.

2.4. Telerehabilitation

Technology in self-rehabilitation has been a growing trend for years and now plays a crucial role in promoting adherence and motivation both for rehabilitation (Arntz et al., 2023; Chen et al., 2019). This evolution of telerehabilitation shows growing acceptance and adoption of technology for remote healthcare delivery (Latifi, 2008; Odetunde et al., 2024; Worlikar et al., 2023). The trend started with basic telemedicine applications, such as live video consultations and remote delivery of rehabilitation services via video, and has progressed to incorporate more sophisticated technologies like remote monitoring, robotics, and virtual reality (Table 4) (Brennan et al., 2009).

Table 4 Overview of Self-Rehabilitation Technologies

Technology	What They Do/Benefits	Challenges	References
Digital Rehabilitation Games	Make repetitive exercises more engaging and motivating. Leverage commercial or bespoke games for stroke rehabilitation.	Limited therapeutic guidance and accuracy with commercial games. Bespoke games require integration with sensors or robotic devices for better tracking.	(Wakabayashi et al., 2021)

Telerehabilitation	Use telecommunication technologies to deliver remote therapy sessions and follow-ups. Reduce hospitalisation duration, costs, and improve access for remote patients.	Lack of physical interaction, technical proficiency requirements for patients, and unresolved policy issues like costs and privacy.	(Borges et al., 2021)
Robotic Devices	Automate therapy procedures and provide optimal therapy doses and intensity using devices like robotic arms or exoskeletons.	Space requirements in home settings and potential safety concerns when used unsupervised.	(Vourganas et al., 2019)
Virtual Reality (VR)	Immerse patients in interactive, computer-generated environments for motor function, balance, gait, and walking exercises.	High cost of VR systems and the need for technical expertise to operate.	(Erhardsson et al., 2020)
Sensors	Measure patients' exercise movements and provide feedback for improved therapy and therapist-patient communication.	Minimising obtrusiveness and validating the accuracy of exercises.	(Maceira-Elvira et al., 2019)
Computer Tablets	Provide a commercially available and affordable platform for rehabilitation exercises and delivering information.	Challenges for stroke survivors with visual field loss or motor deficits.	(Pugliese et al., 2018)
Exoskeletons	Offer improved mobility and support for stroke survivors, facilitating more intensive and functional rehabilitation exercises at home.	High cost and maintenance requirements, with potential challenges in customisation for individual users.	(Shao et al., 2019)
Digital and Mobile Apps	Provide a wide range of interactive exercises, progress tracking features, and communication tools to enhance engagement and adherence to home-based rehabilitation programmes.	Dependence on user proficiency with technology and potential accessibility issues for those with severe impairments.	(Szeto et al., 2023)

Some new emerging technological trends also include Artificial Intelligence and Machine Learning to personalise rehabilitation programmes, provide real-time feedback and predict an individual's progress (Arntz et al., 2023).

2.4.1. What is Telerehabilitation (TR)?

Telerehabilitation (TR), a subset of telemedicine, refers to the remote delivery of rehabilitation services through technologies such as video conferencing, mobile applications, and remote sensing, including the use of wearable devices. This approach allows healthcare professionals to assess, monitor, and provide therapeutic interventions without the need for in-person consultations. The COVID-19 pandemic underscored the importance of TR, as it provided an immediate solution to the widespread need for remote healthcare (Stephenson et al., 2022). TR is particularly advantageous for stroke recovery, where continuity of care is critical, and geographical or logistical challenges can limit access to specialised rehabilitation services. A review by Suso-Martí et al., 2021, highlighted that in-person stroke rehabilitation programmes face dropout rates ranging from 20% to 30%, with transportation issues, fatigue, and low motivation being frequent contributors to this trend (Suso-Martí et al., 2021).

The origins of TR can be traced back to the 1990s, coinciding with the broader development of telemedicine. Initially regarded as experimental, especially in rural areas with limited access to specialised care, technological advancements and the growing demand for remote healthcare have firmly established TR as a key component of modern healthcare systems. Its rapid expansion during the COVID-19 pandemic demonstrated its capacity to deliver effective care remotely, with tools such as video conferencing, remote patient monitoring (RPM), and mobile health (mHealth) helping extend rehabilitation services to underserved populations (Shem et al., 2022).

TR services operate within a framework of clinical, administrative, technical, and ethical principles. Clinicians must be well-versed in telecommunication tools and prepared to address challenges that arise in virtual interactions. From a technical perspective, the reliability and quality of equipment used are crucial to ensure accurate assessments and effective interventions. Ethical considerations centre on patient privacy, confidentiality, and equitable access, particularly in low-resource settings. Administratively, TR must comply with regulations and safety protocols to ensure service integrity (Shem et al., 2022).

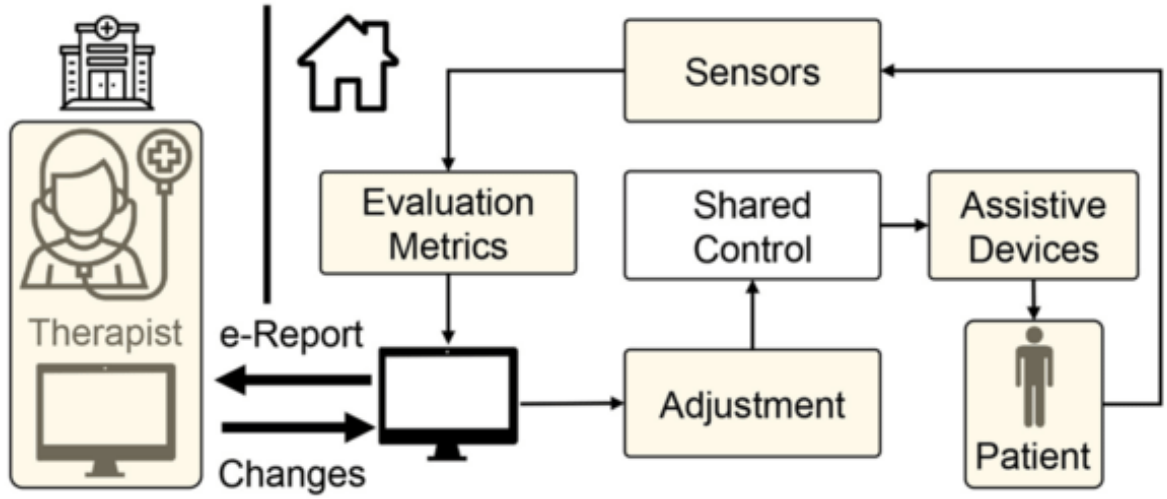


Figure 1: Schematic of TR where patients can continue their rehabilitation with the help of an assistive device while therapist can monitor the progress remotely (Manjunatha et al., 2021).

Research consistently supports the efficacy of TR in stroke rehabilitation. A Cochrane review by Laver et al., 2020, which analysed 22 randomised controlled trials involving 1,937 participants, concluded that TR achieves outcomes comparable to in-person rehabilitation, particularly in improving activities of daily living, upper limb function, and balance (Laver et al., 2020). Knepley et al., 2021 also reported significant improvements in motor function, speech, and patient satisfaction in a study involving 1,025 patients across 34 interventions (Knepley et al., 2021). TR has been shown to not only enhance accessibility but also reduce costs for patients who may struggle to access conventional rehabilitation services. Ventura et al., 2019 observed that under independent task termination (IT) conditions, participants' motor

performance, measured by metrics such as mean speed, peak speed, and path length, improved significantly ($p=.02$ for motor performance and $p < .001$ for productivity) (Barak Ventura et al., 2019). Furthermore, Chen et al., 2020 documented significant improvements in motor function and enhanced neuroplasticity in stroke patients who underwent a 12-week home-based TR programme (Chen et al., 2020).

In addition to its clinical benefits, TR promotes accessibility for underserved populations by integrating real-time feedback and personalised care, which can increase patient engagement and adherence, both critical factors for stroke recovery (Stephenson et al., 2022). Despite the promising evidence, several areas require further research. Long-term studies are necessary to evaluate the sustained benefits of TR beyond the immediate recovery phase, especially concerning cost-effectiveness and long-term functional outcomes (Laver et al., 2020). Furthermore, there is a pressing need for standardised protocols and guidelines to ensure consistent delivery and quality across different populations and settings (Shem et al., 2022). Emerging technologies, such as artificial intelligence and machine learning, hold great potential for delivering more personalised and adaptive rehabilitation programmes, though these areas remain underexplored (Chen et al., 2020). Addressing the digital divide is another priority, as disadvantaged populations must have equitable access to these advancements (Stephenson et al., 2022). Finally, research should focus on integrating TR with traditional in-person care to develop hybrid models that optimise both patient outcomes and healthcare efficiency (Knepley et al., 2021).

2.4.2. The Role of Telerehabilitation in Motivation and Engagement

Telerehabilitation enhances patient motivation and engagement by addressing barriers commonly encountered in traditional rehabilitation settings (Matamala-Gomez et al., 2020; Nicolas et al., 2024). By eliminating the need for travel to rehabilitation centres, TR offers

improved access to care, particularly for individuals in remote or low-resource communities where healthcare services may be limited, but mobile devices are more widely available (Laver et al., 2020; Shem et al., 2022). Cramer et al., 2019, demonstrated that home-based telerehabilitation produces comparable improvements in motor function to in-person therapy, with an adherence rate of 98.3% for telerehabilitation compared to 93.3% for conventional sessions (Cramer et al., 2019).

In a comparative study by Spindler et al., 2019, TR was shown to promote higher levels of autonomous motivation compared to conventional rehabilitation (CR) in cardiac patients (Spindler et al., 2019). Patients engaging in TR reported feeling more in control of their rehabilitation process, attributing this to the flexibility and convenience of remote care, which enabled them to seamlessly incorporate therapy into their daily lives. Importantly, the study revealed no increase in psychological distress in the TR group compared to the CR group, with both groups showing equivalent improvements in anxiety, depression, and quality of life (QoL). This reinforces that TR, despite the lack of face-to-face interaction, maintains the psychological support critical for rehabilitation. Additionally, Ventura et al., 2019, examined motor performance in telerehabilitation and observed improvements in independent task termination (IT). Joint task termination (JT), intended to foster cooperation, led to a notable decrease in user enjoyment ($p=.005$) (Barak Ventura et al., 2019).

Several models have been utilised to evaluate engagement and motivation within the context of telerehabilitation. The Psychosocial Impact of Assistive Devices Scale (PIADS) assesses the influence of assistive technologies on adaptability, competence, and self-esteem (Jutai & Day, 2002). Meanwhile, the User Version of the Mobile Application Rating Scale (uMARS) offers insights into the engagement, functionality, and information quality of mobile health apps (Stoyanov et al., 2016). The Technology Acceptance Model (TAM) investigates perceived ease of use and usefulness, key drivers in the adoption of telerehabilitation tools (Davis, 1989). The

mobile health (mHealth) Technology Engagement Index (mTEI) quantifies the frequency and effectiveness of patient interactions with mobile health technologies, providing a valuable gauge of engagement (Dewar et al., 2016). Finally, the Intrinsic Motivation Inventory (IMI) measures components such as interest/enjoyment, perceived competence, and effort, all of which are essential for maintaining long-term motivation (McAuley et al., 1989; Ryan, 1982).

Interactive telerehabilitation methods, including gamified exercises and virtual reality, have shown to be highly effective in stroke rehabilitation. Chen et al., 2021, reported significant ($p=0.01$) improvements in balance among stroke patients using an exergaming system, as measured by the Berg Balance Scale (BBS, improved by 5 points , based on median values, $p=0.01$) and Timed Up and Go test (TUG, improved by 2.35 seconds, based on median values, $p=0.005$) (Chen et al., 2021). Ciortea et al., 2021, further emphasised that post-stroke patients enrolled in telerehabilitation programmes experienced greater satisfaction and adherence compared to those in conventional therapy, with real-time support and user-friendly interfaces playing crucial roles in maintaining patient motivation (Ciortea et al., 2021).

The levels of engagement and motivation in telerehabilitation can vary depending on whether the patient is in the acute or chronic phase of stroke recovery. During the acute and sub-acute phases (the first six months post-stroke), patients typically display high motivation, as neuroplasticity during this period leads to more noticeable improvements in motor function. Telerehabilitation enables patients to participate more frequently and intensively, with real-time feedback further enhancing motivation (Appleby et al., 2019). In contrast, during the chronic phase, where progress is slower and less apparent, motivation may decline. Patients in this phase may experience frustration due to the limited pace of recovery, which can result in disengagement from therapy. Telerehabilitation has shown promise in mitigating this decline, however, by incorporating engaging, interactive methods such as gamified tasks and virtual reality, which help sustain motivation even when physical gains are less evident (Kerr et al.,

2023). Chen et al., 2019, demonstrated that chronic stroke patients using interactive exergaming were more engaged and adhered more consistently to therapy compared to those following traditional methods, despite the slower physical recovery (Chen et al., 2019).

2.4.3. Collaborative & Cooperative Rehabilitation

Collaborative rehabilitation broadly refers to any therapeutic approach where two or more individuals work together towards a common goal (Sawada et al., 2023). This can involve patients working together, patients interacting with therapists, or even patients engaging with robotic systems designed to foster social interaction. Within telerehabilitation, examples of collaborative rehabilitation can be when patients in different locations connect and engage in shared therapeutic activities through internet-mediated platforms or mobile applications, promoting social interaction and reducing feelings of isolation. It can also take the form of multiplayer games designed for two or more players which promote social interaction, competition, and cooperation, increasing engagement and potentially enhancing motor learning (Johnson et al., 2008). Cooperative rehabilitation which focuses specifically on scenarios where individuals work together in a coordinated manner to achieve a shared objective. This implies a greater degree of interdependence and teamwork compared to collaborative settings, where individuals might have more independent roles. Examples of this include jointly controlling a virtual object in which two patients can be asked to work together to manipulate a virtual object, requiring communication, coordination, and shared effort to complete the task; or assisting each other in a virtual environment (Goršič et al., 2017; Küçüktabak et al., 2021). The idea of incorporating social interaction or ‘play’ into rehabilitation emerged from the mid-2000’s, by examining the influence of a collaborative rehabilitation environment that encourages a long-distance collaborative "play" using two robot-mediated environments and presenting a strategy for increasing motivation on able-bodied persons, applicable to impaired persons, to engage, sustain play and relate during a

shared task (Johnson et al., 2008). Research now, emphasis the potential of expanding collaborative and cooperative rehabilitation to multi-user systems involving networks of individuals interacting through robotic to telerehabilitation devices. Cooperative games, particularly those involving physical interaction and haptic feedback, could be more beneficial for motor learning compared to competitive games as haptic coupling between individuals can enhance coordination, promote error-based learning, and accelerate skill acquisition (Ganesh et al., 2014). Marker & Staiano, 2014, suggest that competition, while motivating for some, can also lead to negative emotions, frustration, and potential for injury if not managed carefully (Marker & Staiano, 2014). Cooperative games mitigate these risks by focusing on collaboration rather than winning or losing. This can create a safer and more supportive environment, particularly for patients who are emotionally vulnerable or have experienced setbacks in their recovery.

Baur et al., 2023 investigated the effects of cooperative versus competitive therapeutic gaming modes on motivation and exercise intensity in individuals with subacute stroke (Baur et al., 2023). They tested four gaming conditions: two-player cooperative, two-player competitive, single-player cooperative, and single-player competitive, with 40 subacute stroke participants. Contrary to their hypothesis, there was no statistically significant difference in self-reported motivation between two-player and single-player modes ($p=0.407$), nor between cooperative and competitive modes ($p=0.415$). While 24 participants preferred single-player modes, only 16 favoured two-player modes, suggesting that subacute stroke patients may favour predictable, computer-controlled opponents over human counterparts. The authors speculated that this may be due to the reduced cognitive demand and greater predictability offered by the single-player format. Participants also rated both single-player competitive and cooperative conditions favourably on measures of enjoyment and effort using the Intrinsic Motivation Inventory (IMI) and Borg Rating of Perceived Exertion (RPE), with no significant difference

in perceived effort across conditions (p=0.943). The study's short duration (only one session per mode) limits understanding of long-term engagement, and the lack of adaptive opponent behaviour in the AI may present a risk for reduced motivation over time due to monotony or insufficient challenge. As the authors noted, future studies should investigate longer-term use and whether opponent behaviour adaptation could improve motivation and exercise adherence over time.

Increasing the number of non-physical interaction channels, such as audio and visual communication, has been shown to increase subject interest and motivation in both competitive and collaborative games as these channels allow for a more engaging and immersive social experience, which can make the games more enjoyable and rewarding. Johnson et al., 2008 had pairs of participants play a competitive tic-tac-toe game while connected to robots (Johnson et al., 2008). There were three conditions: no interaction, audio only, and audio and visual. The results showed that participants were more motivated and engaged when they could see and hear their opponents. This is also supported by Le et al., 2016 who conducted a similar study and confirmed that participants completed their tasks faster when they had both visual and auditory feedback from their partners (Le et al., 2016).

Despite the potential advantages, there is limited research on effective cooperative rehabilitation game designs, particularly those incorporating physical interaction and haptic feedback (Küçüktabak et al., 2021). Future investigations should focus on developing engaging and challenging cooperative games that optimise motor learning and accommodate diverse patient preferences. While some individuals prefer solitary exercises, telerehabilitation can be tailored to meet a range of needs, including an increased demand for multi-player experiences that integrate cooperative elements and appeal to broader stroke populations.

2.5. Measuring Human Movement

Accurately measuring dosage and intensity in stroke rehabilitation is critical for evaluating adherence to clinical guidelines, personalising therapy plans, and objectively assessing patient progress. Additionally, precise measurement is essential for rehabilitation research, where the lack of clear quantification often leads to ambiguity in defining interventions, particularly when studies refer broadly to "standard physical therapy" as the comparator. For new interventions. establishing clear, quantifiable metrics of dosage and intensity allows researchers to consistently compare and evaluate new interventions against well-defined control treatments in randomised controlled trials (RCTs). Movement impairments, particularly affecting gait, are common, resulting in slow, asymmetrical, and abnormal patterns that traditional manual assessments and technology struggle to quantify consistently or accurately. To understand how technology can effectively address these challenges, the following section provides a focused review on the disruption of gait in hemiplegic stroke, current methodologies used to measure impaired movement in stroke populations, and advancements in sensor-based monitoring and wireless system integration.

2.5.1. Disruption of Gait in Hemiplegic Stroke

Accurate measurement of gait rehabilitation progress after stroke is crucial for evaluating recovery and tailoring treatment (Kirdthongkham et al., 2025). Stroke however, disrupts the natural patterns of movement, making precise measurement challenging, especially in real-world settings (Lang et al., 2024).

Post-stroke gait, sometimes referred to as hemiplegic gait when hemiplegia is present, is characterised by asymmetry, reduced speed, shorter stride lengths, and abnormal step patterns (Swaiman & Phillips, 2017). These abnormalities are largely driven by muscle weakness and impaired motor control of the affected side. Weakness, particularly in the lower limb

musculature, results in instability of the body during the single limb stance of gait and decreased ability to generate propulsive force for limb advancement (Swaiman & Phillips, 2017). Consequently, individuals with stroke often adapt their walking pattern by increasing the time spent in stance on the unaffected leg, thereby reducing the reliance on their weaker side and simplifying the control of movement by limiting degrees of freedom (Bassile & Hayes, 2016; Whittle, 2014). Such adaptations produce pronounced asymmetry between the affected and unaffected limbs in step length, stance duration, and joint movements. Additional compensatory behaviours, including hip hiking (elevating the pelvis on the affected side) or circumduction (swinging the leg outward), are commonly employed to achieve safe foot clearance, further complicating accurate, objective measurement of gait parameters such as cadence, stride length, and symmetry (De Quervain et al., 1996).

In addition, altered muscle activation patterns, including spasticity and co-contraction, contribute to asymmetrical movement profiles (Swaiman & Phillips, 2017). Muscles in the affected limb often activate abnormally, either prematurely, delayed, or prolonged, causing a breakdown of the rhythmic patterns of normal gait. The resulting movements lack fluidity, consistency, and predictability (Woolley, 2001) creating measurement challenges..

Hemiplegic gait consumes between 50% and 67% more energy than able-bodied gait (Carmo et al., 2012). This greater effort can quickly lead to fatigue, further increasing gait variability and inconsistency. That variation, combined with a tendency to walk slowly and prefer stable environments, means wearables, or any sensor system, must be both highly sensitive and robust to capture these subtle, non-optimal walking patterns accurately (Renggli et al., 2020). In community or domestic environments, where terrain and context constantly vary, these deviations become even more pronounced, making accurate, objective measurement of rehabilitation dosage and intensity a technical challenge, although clinically important (Lang et al., 2024).

Several studies support a dose-focused approach to gait rehabilitation. For instance, the large sample (n=4909) LEAPS trial provided 36 sessions (approximately 90 minutes each) of intense gait therapy to subacute stroke survivors and found significant gains in walking speed ($p < .0001$, mean change = 0.25 ± 0.21 m/s) and endurance ($p < .0001$, mean increase in walking distance = 81.8 ± 62.8 m); notably, the maximal improvement in gait speed was achieved after around 24 sessions, suggesting a threshold dose needed for optimal benefit (Cramer, 2011; Nadeau et al., 2013; Wolf, 2020). Similarly, a multicentre trial in Canada (n=75) compared higher-dose walking training during inpatient rehab to standard care. People who received increased stepping practice within one-hour physiotherapy sessions (focusing on many repetitions of walking tasks) showed greater improvements in walking endurance (6-minute walk distance) than those receiving usual care (Wolf, 2020).

The dose-oriented perspective is further supported by observational data. In routine stroke therapy, people often perform only approximately 300 walking steps per session, a volume considered insufficient to drive neuroplastic changes and maximise recovery (Cirstea, 2020). The authors recommended an increase in dosage no matter how small to see measurable improvements in walking speed (Cirstea, 2020).

Focusing purely on quantity of steps may neglect practice quality. While increasing walking dosage is a key strategy (especially using treadmills or body-weight support to allow many repetitions), it must be balanced with task specificity and active patient engagement. Treadmill walking, for example, is an efficient way to accumulate steps and is strongly recommended as a mode of repetitive practice (Moore et al., 2022). Improvement from treadmill training may not carry over to overground walking; guidelines, consequently, advise using the treadmill as an additive to overground practice, not a replacement (Moore et al., 2022).

Alternatively, gait can be viewed as an intensity-dependent intervention, in which the effort level or challenge of walking practice is the key driver. In this view, it's not just how much you walk, but how hard you work during walking that matters. Intensity for walking has been referred to as the cardiovascular or muscular demand of training (measured by metrics like heart rate, metabolic work, or walking speed) (Moore et al., 2022). A growing body of research supports the focus of walking intensity over dosage. High-intensity gait training (HIGT), where people practice walking at faster speeds, often aiming for ≥60–80% of heart rate reserve, has been shown in several studies to yield larger improvements in walking function than standard low-intensity rehab (Brunner & Hansen, 2025). Another study directly compared an intensity-focused intervention to a purely dose-focused approach. Thompson et al., 2024, conducted a large sample (n=2385) randomised trial in chronic stroke survivors, assigning participants to: (1) a high-intensity treadmill training programme (walking at 70–80% heart rate reserve) called FAST, (2) a step-count augmentation programme using activity trackers and encouragement to walk more (termed SAM), or (3) a combination of both (FAST+SAM). The results found that all groups showed some improvement, but (Thompson et al., 2024) only those involving high-intensity training achieved clinically significant gains (detail) in walking endurance (6-minute walk distance). The group that only received step-count feedback (SAM) did increase their daily steps substantially, confirming a dose increase, yet this did not translate into meaningful endurance improvement. By contrast, the FAST group (high-intensity exercise) improved cardiovascular fitness and endurance, even though their overall step count didn't rise much (p=0.09).

An intensity-centred approach must, however, contend with issues of feasibility and individual tolerance. Not every stroke survivor can participate safely in high-intensity gait exercises, especially those with comorbidities or high levels of disability. Achieving vigorous exercise intensity can be challenging in practice. Therapists report that getting stroke patients' heart

rates up to high aerobic zones (for example, >70% HRR) is often difficult with conventional methods (Moore et al., 2022). Moore et al., 2022, also highlighted that intensity alone does not address all aspects of recovery, a person might gain speed and endurance through intense treadmill work (improved capacity), yet still not walk more in daily life (performance), due to lifestyle, confidence barriers and lack of skill. The FAST vs SAM trial illustrates this as the high-intensity group improved fitness but did not automatically increase daily walking outside therapy.

Nonetheless, intensity is increasingly recognised as an important parameter effective post-stroke walking rehabilitation, provided it can be delivered in an appropriate and sustainable manner.

2.5.2. Measuring Movement in Stroke with Wearables

Accurate measurement of movement is central to the proposed system's purpose, as it provides an objective way to quantify rehabilitation dosage and intensity in stroke recovery. By tracking movement data, particularly during lower-limb tasks, the dosage and intensity monitor enables a clearer understanding of whether users are meeting recommended therapy targets and allows both users and clinicians to monitor progress over time. This capability is essential not only for supporting self-managed rehabilitation but also for addressing current gaps in research and clinical practice, where therapy is often delivered without precise documentation or standardised measurement. Maceira-Elvira et al., 2019, conducted a review which suggested that wearable devices could successfully track motor functions in real-world environments if utilised and may allow for clinicians and therapists to assess and adjust rehabilitation strategies more precisely (Maceira-Elvira et al., 2019).

Measuring movement and physical activity in stroke rehabilitation can be achieved using various methods, including manual observation, activity diaries, optical tracking systems, and

wearable sensors. Each method has strengths and limitations; however, wearable sensors have emerged as an effective and practical solution for capturing objective and continuous movement data in real-world conditions (Fini et al., 2023). Wearable technology, such as accelerometers, inertial measurement units (IMUs), and physiological monitors, offers significant advantages, including ease of use, unobtrusive continuous monitoring, and the capacity to provide detailed data on activity intensity, duration, and movement quality (Fini et al., 2023). Wang et al., 2017, found that multi-sensor configurations were the most popular type of trunk and upper-limb measurement for rehabilitation and spinal cord injuries with accelerometers and IMUs most frequently used, appearing in 84% (38 out of 45) of the included papers (Wang et al., 2017). These characteristics make wearables particularly suitable for capturing the complexity and variability of real-world stroke recovery movements, enabling clinicians and researchers to obtain accurate and meaningful insights into rehabilitation progress and daily functional activities.

A common challenge in measuring hemiplegic gait with wearable sensors is maintaining measurement consistency, depending on the device, the location and orientation of the sensor will influence the measured signal characteristics. For instance, an accelerometer placed on the shank will produce a different signal pattern compared to one placed on the lower back (Celik et al., 2021). In most research, the preferred location of a single inertial sensor (see Section 2.4 for a further breakdown of differing sensors) for gait assessment is the lower back (3rd to 5th lumbar vertebrae, L3–L5) or feet/foot. This is because the lower back can characterise the overall body motion as the trunk represents the greatest mass.

When measuring whole body movement with a single device, the aim is to have the device as close to the centre of mass as possible to provide a balanced measurement by integrated motion of the body's segments without being overly influenced by isolated limb movements (Chen et al., 2021; Mohan et al., 2021). Sensor placement on the lower back is also comfortable and

unobtrusive for participants which can help to capture natural gait patterns and extend data collection periods. Whilst this sensor location is effective (Prisco et al., 2024), there are a few considerations such as soft tissue movement artefact, displacement of the fixation clothes or strap holding the capture device incorrect sensor alignment due to pelvic obliquities or abnormal foot postures may all introduce sources of error (Celik et al., 2021). If the placement is not consistent across all differing participants, this will directly impact the consistency of output from the algorithms used to extract gait parameters.

Many sensors used to measure gait require initial calibration to establish a baseline measurement and account for individual variations, yet this does not prevent sensor readings from drifting over time due to factors like temperature changes and battery depletion. Researchers can improve accuracy by re-calibration, but this adds further steps to the gait assessment process.

2.5.2.1. Data Processing

When using multiple sensors, synchronising and calibrating them relative to each other is critical. This calibration process is further complicated by factors such as soft-tissue movement of skin-mounted IMUs and slight sensor displacements, which can introduce signal artefacts and reduce the acccuracy of algorithms (Celik et al., 2021). Data and noise reduction algorithms are likewise affected: Yi et al., 2018, found that the fusion coefficient of a complementary filter was overly sensitive, necessitating additional operations, while Nazarahari & Rouhani, 2021, reported that algorithms such as extended Kalman filters and complementary filters often require offline calibration and vector selection to reject imperfect measurements (Nazarahari & Rouhani, 2021; Yi et al., 2018). Although these techniques can produce high accuracy in controlled conditions, translating them to everyday use, especially for individuals with lower technological skills or communicative and cognitive impairments, remains difficult. Furthermore, many algorithms rely on thresholds to identify peaks in sensor

signals for initial contact (IC) and final contact (FC) events. Thresholds that work for healthy individuals may not apply universally across different populations or walking speeds, potentially causing inaccuracies in phase estimations.

Environmental factors such as walking surfaces, footwear, and the use of mobility aids also pose challenges to the remote collection and analysis of gait data. As individuals, particularly those with stroke, move between harder and softer surfaces or uneven terrains, they naturally adapt their step length, cadence, and joint kinematics (Celik et al., 2021; Celik et al., 2022). Distinguishing between these normal adaptations and pathological gait abnormalities can be difficult, complicating the detection of IC and FC events. Algorithms designed and trained predominantly on level walking data may perform poorly under real-world conditions where floors are uneven, or mobility aids alter gait dynamics (Chandler et al., 2021). The diverse gait patterns found in stroke populations, each with their own unique timing and sensor-signal shapes, often exacerbate these issues, as algorithms trained on healthy cohorts do not generalise well (Celik et al., 2022). The absence of standardised protocols for sensor placement, signal processing, and algorithm validation further limits cross-study comparability and the generalisability of findings.

Capturing and analysing lower-limb or gait movement patterns in people with requires combining biomechanical principles and engineering solutions. Effective monitoring devices designed for hemiplegia can help address these biomechanical and technological hurdles. By also using specialised algorithms and robust hardware design, these devices can accurately track recovery progress, support therapy, and improve the quality of life for stroke survivors.

2.5.3. Sensor-Based Activity Monitoring and Data Processing

2.5.3.1. Overview

Accurate activity monitoring of movement, including rehabilitation activities relies on multi-sensor fusion. The most common sensors used are accelerometers, gyroscopes, and magnetometers, either as individual units or combined into an Inertial Measurement Unit (IMU) (see Table 5). Single or combined data from these sensors forms the basis of robust motion tracking in hemiplegic stroke populations. Raw data from these sensors typically includes noise and drift, making signal processing essential for reliable interpretation.

Sensor Type	Principle	How It Works	Data Utility	Algorithms/Equations	Benefits	Limitations
Accelerometers	Measure linear acceleration along one or more axes (x, y, z).	Detects changes in velocity along each axis to identify patterns and peaks in acceleration.	Step detection, cadence measurement, movement intensity estimation.	Step Detection: Peak detection algorithms using thresholds, Cadence = Peaks / Time (steps/minute), Energy Expenditure = $\int\|a(t)\|dt$	Low cost, widely available, and highly sensitive to movement; effective for step detection and cadence measurement.	Sensitive to noise and gravity effects; may require filtering for accurate results.
Gyroscopes	Measure angular velocity (rotational speed) around one or more axes.	Tracks angular velocity changes, differentiating between rotational movements along different axes.	Orientation tracking, gait phase detection, compound activity identification.	Gait Phase Detection: Threshold-based algorithms for angular velocity peaks, orientation using Euler angles: $\theta(t) = \theta(0) + \int\omega(t)dt$, Sit-to-Stand Detection: Pattern recognition algorithms.	Accurately captures rotational movements and complements accelerometers for orientation.	Prone to drift over time; requires fusion with other sensors for stable orientation.
Magnetometers	Measure the local magnetic field vector for orientation correction and drift compensation.	Measures magnetic field strength and direction to provide heading and orientation correction.	Heading measurement, drift correction, spatial context detection (e.g., turning).	Drift Correction: Kalman filters or complementary filters integrate magnetometer data with gyroscopes and accelerometers to stabilise heading, Heading Calculation: heading = arctan(By/Bx)	Corrects sensor drift, provides directional context, and improves fusion accuracy.	Susceptible to magnetic interference, reducing accuracy in certain environments.

2.5.3.2. Signal Filtering Techniques

The high-frequency noise caused by soft tissue movement or sensor displacement can be removed through low-pass filtering techniques which allows the low-frequency signals of movement (typically under 4Hz) to pass through while attenuating, or blocking, the higher frequencies associated with movement artefacts (Tong & Granat, 1999). Accelerometers measure linear acceleration, which can be used to determine inclination, with respect to gravity, directly without integration. Therefore, they are less prone to drift and so benefit the most from low-pass filtering (Alonge et al., 2014).

The Butterworth filter (Thompson, 2014), is the most common choice of low-pass filter in movement studies and its characteristics (e.g. sharply it cuts off high frequencies) can be determined by its cut off frequency (Celik et al., 2022). Tong and Grant, 1999, used a cut off frequency of 4Hz to smooth gyroscope signals recorded from walking before analysing angular velocity patterns, however other studies have used a 5Hz to prioritise removal of high-frequency noise from accelerometer data (Tong & Granat, 1999; Zhang & Zhang, 2022).

In contrast, high-pass filtering removes low-frequency components and are more commonly used in gyroscopes. Gyroscopes, when integrated to derive orientation, often exhibit drift, a gradual accumulation of error that manifests as a slow, low-frequency shift in the signal baseline. Applying a high-pass filter can remove this drift by attenuating these low-frequency errors (Camargos et al., 2009).

Tong and Grant, 1999, used a high-pass filter with a 0.3Hz cut-off frequency to specifically correct the drift of shank inclination derived from gyroscope data (Tong & Granat, 1999). High-pass filters can also highlight gait phases such as foot impacts which generate transient high-frequency components. Norris et al., 2014, suggested that when studying the impact forces

during running that the researcher might use a high-pass filter to focus on the sharp acceleration peaks at heel strike (Norris et al., 2014).

2.5.3.3. Sensor Types and Applications

Accelerometers and gyroscopes can be used on their own or combined using sensor fusion to produce movement pattern data. Whilst it is acceptable to use single sensors if it fits the requirement, research has shown that using both accelerometers and gyroscopes in a combined unit leads to more accurate measurements of temporal and spatial running parameters compared to using a single sensor type (Norris et al., 2014).

Algone et al., 2014, used a sensor system with accelerometers and gyroscopes to estimate hip and knee angles and found that combining the sensor data through a complementary filter improved accuracy compared to using individual sensors (Alonge et al., 2014). Mohan et al., 2021, has countered this by demonstrating that a single IMU combining accelerometers, gyroscopes, and magnetometers could effectively estimate both spatial and temporal gait data (Mohan et al., 2021).

2.5.3.4. Sensor Fusion and Algorithms

Sensor fusion algorithms, such as Kalman and complementary filters, address the limitations of individual accelerometer and gyroscope measurements by combining both sources to produce more accurate movement estimates.

Kalman filters employ an iterative process that reduces measurement uncertainty, making them especially effective in complex or noisy conditions. Although they are more computationally expensive, they provide stable, precise estimates of position, velocity, and orientation. Complementary filters, by contrast, are computationally simpler: they use a high-pass filter on the gyroscope data and a low-pass filter on the accelerometer data, then merge these filtered

signals to estimate orientation. This approach works well for relatively slow and smooth movements (Alonge et al., 2014).

Using multiple sensors, however, presents challenges, particularly in complexity, cost and practicality. Integrating and processing data from multiple sensors requires complex algorithms and hardware, meaning that the system has a much higher processing requirements and thus has to have a more complex system to accommodate this which can be more expensive than a single sensor system (Tong & Granat, 1999). The choice between individual sensors and combined sensors using sensor fusion depends on the specific application and the desired level of accuracy and reliability. For simple applications where cost and practicality are primary concerns, individual sensors might suffice. For more demanding applications where accuracy is paramount, such as clinical gait analysis, sensor fusion offers important advantages.

2.5.3.5. Advantages and Limitations of Gyroscopes

While combining accelerometers and gyroscopes remains standard practice in gait analysis, a single gyroscope system can be advantageous in certain applications. Because gyroscopes measure angular velocity directly, they are unaffected by gravity and linear acceleration, making them particularly useful for measuring inclination and joint angles (Tong & Granat, 1999). This is beneficial in movements such as walking, where accelerometers often conflate gravitational and translational acceleration.

Gyroscopes are also adept at capturing cyclical patterns by detecting repetitive rotations of body segments, enabling accurate step identification and cadence calculation (Alonge et al., 2014). Consequently, algorithms that rely on angular velocity for IC and FC detection tend to be less sensitive to sensor positioning than acceleration-based methods. Additionally, sensor placement anywhere along the same anatomical plane produces almost identical signal outputs (Celik et al., 2022).

For people with stroke, studies have used gyroscopes to evaluate gait characteristics including step count, cadence, and gait asymmetry, demonstrating feasibility in this population (Celik et al., 2021; Celik et al., 2022; Mohan et al., 2021). Using a single IMU for abnormal gait characterisation, however, can be challenging when not placed on the trunk; thigh-mounted IMUs, for instance, exhibit greater angular velocity variability due to soft-tissue movement (Tong & Granat, 1999). At the same time, thigh placement allows monitoring of knee angle kinematics, a crucial parameter in stroke gait analysis.

2.5.3.6. Feature Extraction Techniques

Once raw signals are recorded and cleaned, the next stage is feature extraction. This stage differentiates exercise movements and prepares the data for classification or segmentation algorithms.

Peak and valley detection is commonly used to identify repetitive patterns, such as step counting by detecting peaks in vertical acceleration signals. A peak in the vertical acceleration signal can indicate the moment when the foot leaves the ground (toe-off), while a valley can indicate the moment when the foot makes contact with the ground (heel strike), this pattern can then be segmented into individual steps and count the number of steps taken (Cornish et al., 2024; Li et al., 2019).

Peak and valley detection alone may not be sufficient enough to accurately identify steps, especially in noisy signals or when the pattern is not well-defined. To improve accuracy, Holm et al., 2023 recommended that the time difference between two peaks for the same activity will be relatively fixed if it takes place at the same speed and so this constraint could be included into the segmentation (Holm et al., 2023). Additionally, they recommended the continuity of the number of neighbouring windows of acceleration surpassing a threshold to form bouts of gait over a certain period could also be considered.

A common issue with thresholding approaches is that the thresholds must be adapted based on gait velocity and other gait and sensor characteristics. In step counting, the minimal distance between two peaks needs to be adjusted based on the walking speed and if the minimal peak distance is too large, the counter will skip steps, while a small value may cause over-counting. Therefore, adaptive algorithms are often used to adjust the thresholds based on the characteristics of the signal (Pham et al., 2018).

Finite state machines (FSMs) can be used to identify more complex patterns in gait data by using a set of states and transitions to model the different phases of the gait cycle (Cornish et al., 2024; Wang et al., 2024). These methods of FSM and thresholding are not limited to step counting and can be applied to a wide range of repetitive movement patterns, including those common in stroke rehabilitation such as sit-to-stand transitions or cycling. In populations with hemiplegia, where movement patterns are often irregular, asymmetric, or slower than typical, FSMs offer a flexible framework for capturing these deviations by allowing transitions between states to be tailored to atypical timings and amplitudes. When combined with time intervals between peaks, these techniques can also estimate cadence (e.g., steps or repetitions per minute), making them particularly valuable for quantifying intensity in stroke populations where conventional algorithms may fail due to variability in movement execution.

Tahsin et al., 2024 investigated the use of time domain features in calculating stroke rehabilitation activity, they found that the mean can provide a measure of the average amplitude of the signal over a given time window, with a higher mean value generally indicating a greater overall level of activity (Tahsin et al., 2024).

The root mean square (RMS) is a measure of the average power of the signal and can be used for signals with both positive and negative values, as it represents the magnitude of the signal, regardless of its direction, with a higher RMS indicating more intensive activity. The standard

deviation (SD) quantifies the spread of the signal values around the mean and so this provides a measure of the variability or inconsistency in the signal, with a high SD indicating more variability in the activity pattern.

Doulah & Iqbal, 2012, also highlighted that Zero-crossing rates (ZCR) can be helpful in identifying repetitive phases in movement data by tracking shifts and the direction and frequency of these shifts within a signal (Doulah & Iqbal, 2012). The ZCR measures how often a signal crosses the zero-amplitude line, and so a higher ZCR indicates more frequent direction changes, suggesting more dynamic movement (Fattah et al., 2012).

The swing phase of gait involves greater acceleration magnitude and more changes in angular velocity than stance, producing higher ZCR. During STS, the rising phase involves a clear upward acceleration followed by deceleration as the person approaches a standing position, causing a peak in the ZCR around the point of transition from acceleration to deceleration. When sitting back down, this would in turn cause a peak corresponding to the shift in acceleration direction. An algorithm might use a combination of a low ZCR and a mean acceleration close to the gravitational acceleration to identify the stance phase in gait (Wang et al., 2024). Similarly, a high ZCR coupled with a high RMS value in the vertical acceleration signal could indicate the upward movement during an STS transition.

2.5.3.7. Segmentation and Outlier Detection

Segmentation and outlier detection are essential for reliable gait event identification and parameter calculation. Outliers may stem from sensor malfunction, loose attachments, or atypical movements due to gait impairments. Although filtering helps remove noise, threshold-based approaches can also yield robust results. For instance, Laidig et al., 2021 propose an adaptive threshold method that iteratively refines boundaries using weighted averages of angular velocity maxima and minima, thereby isolating stationary phases more accurately

(Laidig et al., 2021). Wang et al., 2024 build on this with the Peak Width Threshold (PWT) approach, which analyses the width of peaks in angular velocity signals to differentiate between true peaks which indicate non-stationary phases, and short, transient rotations that can confuse conventional segmentation (Wang et al., 2024). Re-segmenting the gait cycle in this manner helps ensure no genuine peaks remain in the stationary phase. Nevertheless, such methods have limitations in specific populations. Lum et al., 2020, for example, show that a counts threshold applied to accelerometery data in stroke patients is more sensitive to non-functional movement than functional movement in the paretic limb, highlighting challenges when applying these thresholds to hemiplegic gait (Lum et al., 2020).

Summary

In summary, sensor-based activity monitoring of rehabilitation is promising, but necessitates a synergy of robust hardware (accelerometers, gyroscopes, magnetometers) and sophisticated data processing pipelines. Advanced signal processing enables the accurate detection of steps, cadence, exercise repetitions, and functional transitions like STS. This is critical for tracking rehabilitation dosage and intensity, ensuring that people receive timely feedback and clinicians gain objective data on patient progress. By carefully tailoring sensor choice, processing algorithms, and computational workflows, it is feasible to build a wearable system that can capture and categorise the unique motion profiles of hemiplegic or other mobility impaired individuals, delivering objective and automative real-time gait tracking.

2.5.3.8. Intensity Tracker Design Choice

The DAIM intensity wearable will rely solely on a gyroscope to monitor rehabilitative movements. This decision was informed by the nature of hemiplegic gait, which is typically slow, inconsistent, and prone to abrupt compensatory actions such as hip hiking or circumduction. These movement characteristics can lead to poor signal quality and excessive

noise in accelerometer data, particularly when measuring low-speed or irregular motion. In contrast, gyroscopes directly measure angular velocity, which provides more stable and interpretable information for detecting the rotational aspects of movements such as sit-to-stand or cycling. As shown in Table 5, gyroscopes are widely used in stroke populations due to their robustness in scenarios where linear acceleration data are unreliable. By simplifying the sensor configuration to a single gyroscope, the DAIM system improves wearability, reduces processing complexity, and maintains sufficient accuracy for tracking the intensity of rehabilitation movements in real-world stroke recovery settings.

2.5.4. Wireless Data Collection and System Integration

2.5.4.1. Overview

Near Field Communication (NFC) is a short-range, wireless connectivity technology that enables communication between devices over short distances (Sethia et al., 2019). NFC evolved from Radio Frequency Identification (RFID) technology, and enables short-range wireless communication at 13.56 MHz within a 10 cm range, at rates up to 424 Kbit/s (Morak & Schreier, 2015). NFC is a two-way interaction technology, meaning it can both read and write data and is widely used in modern society for contactless payment

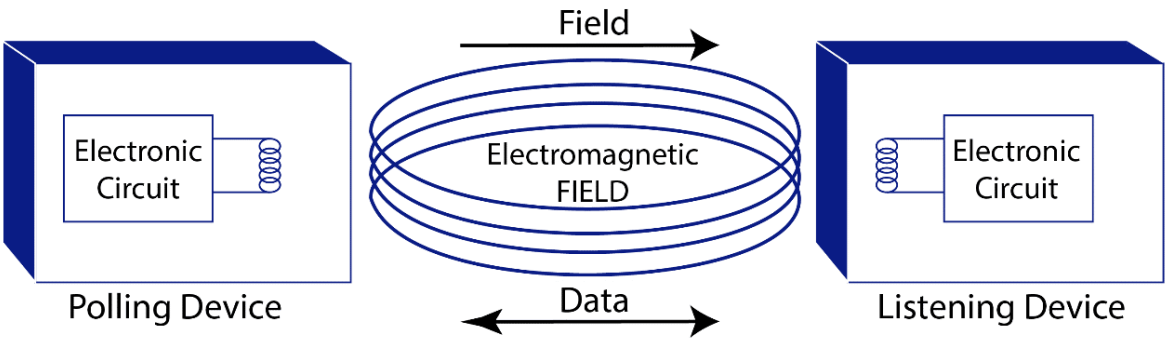


Figure 2 NFC Diagram (Garcés, 2023)

NFC systems involve an initiator (reader) and a target (tag), operating either in active or passive mode. They support three interaction modes (Bravo et al., 2008):

- Card Emulation: NFC device mimics a contactless smart card, typically used in payments and ticketing.
- Peer-to-Peer: Two NFC devices exchange data directly, such as contact info or small files.
- Reader/Writer: NFC device reads data from passive NFC tags, used in logging or tracking scenarios.

NFC offers quick, secure, and user-friendly communication. Its short range provides a layer of security by reducing the risk of unintended connections. Additionally, NFC remains compatible with existing RFID infrastructure, increasing its versatility. Users benefit from automatic pairing and seamless initiation of interactions simply by bringing two NFC-enabled devices into proximity.

2.5.4.2. Applications in Healthcare

NFC has proven valuable in healthcare for enhancing safety, efficiency, and user engagement (Alzahrani & Alnfiai, 2022; Sethia et al., 2019). Alzahrani & Alnfiai, 2022, integrated NFC tags into prescription packaging to deliver medication details in patients' native language. They found that over 57.1% of pharmacists would want to use the application if it were up to them, and over 57.1% were satisfied with the application, with 71.4% preferring the system to prior methods (Alzahrani & Alnfiai, 2022). Sethia et al., 2019, developed the S-MAPLE health folder, a mobile-based contactless health record system using NFC in Host Card Emulation (HCE) mode. It enabled patients and healthcare professionals to securely access and manage distributed medical records via an encrypted cloud-based service (Sethia et al., 2019).

In telerehabilitation, NFC facilitates intuitive "tap-and-go" interactions that support patient engagement, especially among the elderly or cognitively impaired (Bravo et al., 2008; Chen et al., 2016; Guía et al., 2013). Bravo et al., 2008, used NFC to help caregivers manage

Alzheimer's patients' schedules, reducing documentation workload and freeing time for direct care. Primary users of the NFC-enabled mobile phones for information management were the day centre assistants and other healthcare professionals, not the Alzheimer's patients themselves. It can therefore still be argued that the burden of data collection is placed on the AHPs and if the system still requires supervision under operating, it could be hypothesised that AHPs would prefer the original data collection methods.

NFC also enhances gamification and attendance tracking in therapy settings. Chen et al., 2016, embedded RFID readers in upper-limb rehabilitation devices to support data collection and recovery tracking. De la Guía, Lozano, and Penichet, 2013, implemented NFC in collaborative cognitive rehabilitation games, reducing cognitive load and encouraging social interaction.

2.5.4.3. Data Transmission Methods

Integrating NFC data into electronic databases typically involves using microcontrollers (e.g., Arduinos) equipped with Bluetooth or Wi-Fi capabilities. These wireless technologies enable seamless data transmission from the NFC reader to a mobile app or directly to an online database for real-time analysis and storage. Bluetooth can provide a short-range, low-power connection to smartphones and tablets, facilitating immediate data transfer. Meanwhile, Wi-Fi offers a wider range and higher bandwidth, allowing for rapid synchronisation with cloud-based database or remote servers. If a mobile phone serves as the NFC reader, data can be automatically transferred to an app for subsequent synchronisation and processing (Iglesias et al., 2009). In systems that gather input from multiple sensors and NFC devices, once the data is captured, it must ultimately be transmitted and synchronised through a central database or platform to provide an accurate picture of the data captured.

Real-time data transmission over Wi-Fi is typically managed by sending messages as IP packets, which makes performance dependent on network stability. Congestion and packet loss

can cause delays and disruptions in real-time applications (Calvaresi et al., 2017). Additionally, these applications may require high bandwidth to handle large data volumes at speed. Bluetooth Low Energy (BLE) output, meanwhile, can limit the maximum sampling frequency, especially when multiple nodes are connected.

2.5.4.4. Challenges in Real-Time Data Systems: Power Consumption and Sampling Rates

The most critical parameter influencing BLE output is the Connection Interval, which determines how frequently communication occurs. According to BLE specification, the minimum valid Connection Interval is 7.5ms (Buonocunto et al., 2018). High sampling rates may will also impact battery life with higher power consumption linked to more frequent measurements. Buonocunto et al., 2018's stroke telerehabilitation platform found that decreasing the frequency from 200Hz to 50Hz would quadruple the power consumption by the IMU sensor (Buonocunto et al., 2018). Bobin et al., 2016's platform also experienced a significant decrease in battery life, from three hours to half an hour, when the LEDs, which require high current, were activated for orientation tracking (Bobin et al., 2016).

Adaptive or dynamic sampling rates could help mitigate this by providing periods of low sampling when the user is inactive or when high precision is not critical (Rienzo et al., 2020). Synchronisation issues may also occur due to clock drift and variations in latency which will cause misalignment in delivered data.

Depending on the complexity of the algorithms, real-time data processing may also demand significant computational resources. Limited processing power, memory, or storage capacity can create bottlenecks, affecting the system's ability to handle the data flow (Calvaresi et al., 2017). In cases of network interruptions, data could be cached locally within the microprocessor until connectivity is restored, however this would imply that the

microprocessor has storage capabilities. The S-MAPLE health folder and Cognitive NFC game studies both required that data as stored locally to enable quick access when offline.

2.5.4.5. Challenges in Real-Time Data Systems: Synchronisation Rates

To ensure the correct data synchronisation, periodic synchronisation has been adopted in research, Bobin et al., 2016, monitored and guided the ADL sing a smart glass (SyMPATHy) in which data was logged locally then sent to a computer database once a day or once a week (Bobin et al., 2016). Similarly, Buonocunto et al., 2018's limb tracking telerehabilitation platform had the synchronisation of the clocks in the sensor nodes repeated periodically every 8 minutes to maintain accurate time alignment (Buonocunto et al., 2018). Event triggered synchronisation is a technique in which data synchronisation is initiated when specific events occur, such as changes in data values, user actions, or system triggers, minimising unnecessary data transfers. Barman et al., 2012's RFID system to monitoring arm activity took data from proximity and movement sensors and synchronised them using time and ID stamps as keys (Barman et al., 2012).

2.5.4.6. Challenges in Real-Time Data Systems: Latency

Latency is also a critical factor in real-time systems. Buonocunto et al., 2018's stroke telerehabilitation platform highlighted that a high latency can lead to a sluggish and unresponsive system which directly impacted users by disrupting the natural flow of the exercise and thereby reduced the effectiveness of the therapy (Buonocunto et al., 2018).

There is, however, an acceptable latency threshold, but it will vary depending on the specific application and nature of the data feedback. In applications like healthcare monitoring systems that generate alerts or warnings, a delay of a few hundred milliseconds might be tolerable.

Latency can arise from the time it takes for sensors to acquire data and for the system to process that data, but also from communication delays introduced by data transmission over networks,

particularly in wireless systems. As previously mentioned, in a BLE-based sensor network, the Connection Interval will impact the data output and thus introduce latency. Primary mitigation strategies include minimising the amount of data transmitted by employing techniques like differential synchronisation (Blas et al., 2021).

Differential synchronisation focuses on transmitting only the changes or differences in data since the last synchronisation event. Instead of sending the entire dataset, only the modified portions are transferred which can significantly reduce the amount of data transferred when only small portions of the dataset have changed and conserves bandwidth and transmission time. The use of a dedicated real-time protocol alongside BLE for clock synchronisation can improve predictability in a sensor network by prioritising timely data delivery (Buonocunto et al., 2018; Calvaresi et al., 2017). Addressing the sampling rate of the IMU will also directly impact the latency, with a lower sampling rate producing a lower latency.

2.5.4.7. Summary

NFC technology is a suitable way to pair wearable sensor movement intensity with dosage by seamlessly identifying exercise equipment and context, whilst robust connectivity algorithms ensure that said dosage and intensity data is uploaded and synchronised within secure servers to deliver reliable, real-time feedback to users. This data integration will enable a more effective form of remote monitoring, adherence tracking, and personalised intervention adjustments in stroke rehabilitation and guidelines.

2.6. Chapter Summary

This chapter has explored the diverse dimensions of stroke, how it is managed within the NHS and recommended guidelines, the current engineering challenges, and potential technological solutions to enhance self-rehabilitation. The research indicates that definitions of ‘dosage’ and ‘intensity’ differ among healthcare practitioners, researchers, and UK guideline frameworks;

nevertheless, self-rehabilitation, whether practiced at home, on acute wards, or in community settings, has become an increasingly popular method of improving cognitive and motor recovery. Consequently, the responsibility of meeting the recommended three hours of multidisciplinary therapy a day is shifting from NHS practitioners to the individual with stroke.

Despite this growing emphasis on patient-led care, the lack of a standardised measurement system for stroke recovery and the slow adoption of modern technologies within the NHS have led to fragmented data collection. Clinicians largely rely on manual or outdated methods, especially during the chronic phase, which often reduces logging to six-monthly reviews. Such data, though vital for SSNAP and SSCA audits, remains incomplete and inconsistent, ultimately influencing how stroke care is delivered across the UK.

To address these limitations, telerehabilitation systems are needed that can provide a subjective yet automated method for monitoring a person's rehabilitation, as well as signposting, encouragement, and motivation to maintain therapy activities as they reintegrate into daily life. This device must be versatile enough to fit into any environment from acute to chronic care, ideally remaining low-cost, lightweight, and portable. It should also meet the clearly defined user requirements associated with communicative and cognitive impairments often present in this population. In doing so, the device should consider the new approaches to telerehabilitation by incorporating multi-player cooperative gaming within its platform so to promote motivation and adherence with the aim to encourage those who can self-rehabilitate to work with their healthcare practitioners to meeting the new National Clinical Guidelines for Stroke.

By achieving this, the NHS and stroke survivors alike can collaborate to build a more accurate understanding of how much true rehabilitation takes place, ultimately guiding the continued refinement of UK stroke guidelines and highlighting areas in need of further improvement

whilst also promoting self-rehabilitation within the user via the implementation motivation and social features.

The following chapters of this thesis will consider these points in the design and development phases. A co-design approach will be employed to obtain a unique perspective on the requirements of a design, based on the experiences of stakeholders with existing devices and their self-rehabilitation journey.

2.6.1. Objectives

Following this review of relevant literature the objectives of this PhD thesis are now:

- Determine the design specifications of a dose and intensity monitoring system, using a user-centred design approach by collaborating with stroke survivors and clinicians via focus groups, interviews, surveys and iterative feedback during development.
- Develop a dosage tracking prototype and test functionality, accuracy and feasibility on chronic and acute stroke survivors in both clinical and research settings. Followed by any modifications based on feedback.
- Develop an intensity tracking prototype and test functionality, accuracy and feasibility on chronic and acute stroke survivors in both clinical and research settings. Followed by any modifications based on feedback.
- Develop a mobile application and test functionality and useability.
- Conduct a study to test entire functionality of prototype system to test acceptability.
- Make recommendations for future development of the system

Chapter 3. Co-Design of a Dosage and Intensity Monitor

3.1. Introduction

Chapter 2 reviewed the existing literature on current methods for tracking and measuring rehabilitation intensity and dosage within clinical and research settings, highlighting its growing importance in the context of updated clinical guidelines. This review identified critical gaps, notably the lack of standardisation in current practice, and emphasised the potential of telerehabilitation approaches to bridge these gaps, particularly through accurately tracking lower-limb rehabilitation exercises and rehabilitation dosage within stroke populations.

In alignment with the 'Development of an Intervention' phase of the Medical Research Council (MRC) framework (Skivington et al., 2021), this chapter describes a co-design study aimed at capturing the views, experiences, and preferences of stroke survivors and other key stakeholders. The central goal was to collaboratively define clear design criteria and engineering requirements for the proposed dosage and intensity monitoring system (Johansson et al.; Kerr et al., 2024; Nasr et al., 2016; Olafsdottir et al., 2020). These criteria will directly inform subsequent developmental stages outlined in Chapters 4-6.

This chapter details the study's specific aims, outlines the methodological foundations and research design, explains participant recruitment strategies, data collection, and analytical processes, and concludes with definitive final device specifications, alongside a discussion of the key findings.

3.2. MRC Framework for the development of complex interventions

The MRC framework is a widely used guidance for developing and evaluating "complex interventions" in health and social care services, public health practice, and other areas that affect health. The framework aims to help researchers collaborate with stakeholders to identify key questions about complex interventions and design and conduct research using diverse perspectives and appropriate methods (Skivington et al., 2021). The MRC originally published guidance for developing and evaluating complex interventions in 2000, with revised guidance following in 2006. Since 2006, significant conceptual, methodological, and theoretical developments have occurred resulting from a full-day workshop in May 2018 involved 36 participants to discuss topics identified in a gap analysis. The framework was redrafted based on the findings from this and additional interactive workshops and was followed by a final expert review. The entire process was overseen by a scientific advisory group and reviewed and approved by relevant MRC and National Institute for Health and Care Research (NIHR) bodies before external peer and editorial review. The new framework was finally accepted in August 2021 and is the current up-to-date framework (Figure 3).

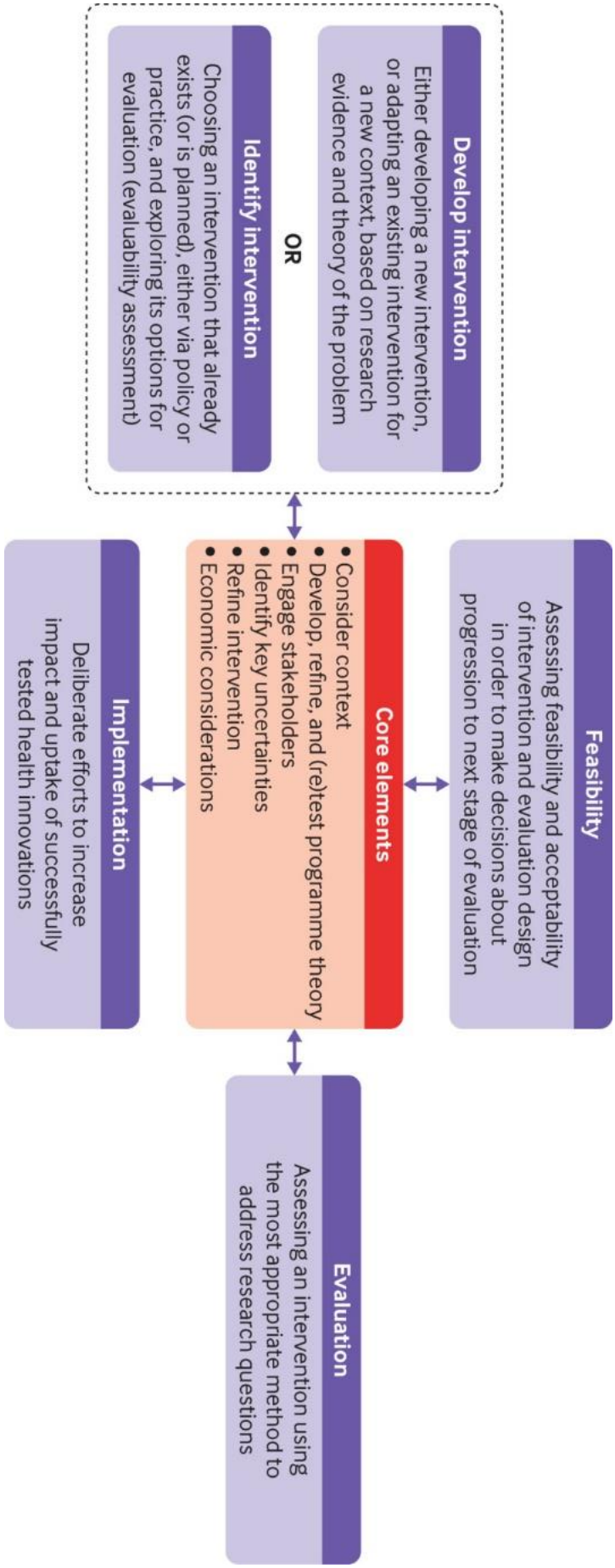


Figure 3 MRC Framework (Skivington et al., 2021)

This provides structured guidance for developing and evaluating complex interventions. It supports an iterative process through distinct but interconnected phases, all while continuously addressing a core set of elements: understanding context, developing and refining programme theory, engaging stakeholders, identifying key uncertainties, refining the intervention, and considering economic implications. These principles help ensure that interventions are both evidence-based and contextually appropriate. The framework outlines four main phases: development or identification of the intervention, feasibility, evaluation, and implementation. These phases are not strictly linear and can be revisited as needed, depending on the research context and level of existing knowledge (see Figure 3).

The development or identification phase involves designing a new intervention or adapting an existing one for a specific context, grounded in theoretical frameworks and existing evidence. It also includes reviewing current practices (such as existing policies) and determining their evaluability.

The feasibility phase explores the practicalities of delivering the intervention and assessing its acceptability. It aims to resolve uncertainties related to recruitment, data collection, participant retention, intervention adherence, and potential costs. Evaluability assessments may be conducted here to decide whether a full-scale evaluation is worthwhile and feasible.

The evaluation phase involves assessing the intervention using appropriate research methods to address not only its effectiveness but also its mechanisms of action, contextual influences, and broader system-level impact. This may include mixed-methods studies, natural experiments, or process evaluations to examine fidelity, engagement, and underlying mechanisms of change.

Finally, the implementation phase focuses on scaling and embedding the intervention in real-world practice. It considers the factors that enable or hinder widespread adoption, including

the flexibility needed to adapt the intervention across different settings and populations. This phase aims to support sustainable uptake by aligning strategies with the realities of practice and policy environments.

The MRC framework was selected as the guiding structure for the DAIMs development due to its comprehensive, flexible, and evidence-based approach to developing complex health interventions. Given the multifaceted nature of stroke rehabilitation, which involves behavioural change, technology integration, and stakeholder engagement, the MRC framework offers a robust structure for iteratively designing, testing, and implementing the DAIM system. Its emphasis on context, stakeholder involvement, and ongoing refinement aligns well with the co-design methodology adopted in this project and ensures the intervention is both user-centred and grounded in practical feasibility.

3.3. Co-Design

'Co-Design', as a method in design research, developed from an evolving landscape in which design researchers have progressively moved closer to the people for whom they are designing; whereas 'co-creation' has been described as any act of collective creativity involving two or more people (Sanders & and Stappers, 2008). Within this loose frame, co-design is a specific instance of co-creation applied across the entire span of a design process, where stakeholders collaboratively shape design concepts and solutions together with designers. In this co-design sense, "users" are no longer passive subjects but are regarded as experts of their experience, engaging in creative activities alongside trained designers throughout the development process (Sanders & and Stappers, 2008).

Further research clarifies the participatory ethos implied by the "co" in co-design. It has been emphasised that co-design is not just about involving patients as informants or consultants but about establishing partnership and shared leadership between patients and healthcare

professionals throughout the improvement process (Bate & Robert, 2006). In this framework, healthcare staff and service users work collaboratively so that each can input their perspectives and experiences on level terms, with professionals and service users jointly shaping service design. However, there is a boundary within this clarification in which this does not mean attempting to make service users design or healthcare experts; patients are included primarily for their first-hand, lived experience, which offers unique insights that cannot be obtained from professionals alone. This lived experience is what makes co-design distinct from other participatory approaches that involve users only as sources of feedback or verification of a predetermined and constructed device.

This thesis will follow the definition of co-design as the "active collaboration between stakeholders in the design of solutions to a pre-specified problem" (Vargas et al., 2022). The same paper also defines co-creation as "the collaborative approach of creative problem solving between diverse stakeholders at all stages of an initiative, from the problem identification and solution generation through to implementation and evaluation" and co-production as "implementing previously determined solutions to a previously agreed problem with emphasis on the most efficient use of existing resources and assets" (Vargas et al., 2022). Whilst this thesis does demonstrate a collaborative approach to the design, implementation and evaluation of the proposed device in line with the criteria of co-creation, a key distinguisher is that it surrounds a 'prespecified problem' rather than going through problem identification with the stakeholder, thus the project aligns with the co-design definition.

A 2024 scoping review found that many stroke interventions now explicitly use co-design, especially technology-based solutions (which accounted for 65% of co-designed interventions) (Singh et al., 2024).

Some researchers have noted that whilst qualitative studies are important in the co-design and development of stroke rehabilitation devices, technological solutions are frequently developed and tested with minimal input from the end-users (both stroke survivors and AHPs) (Shah & Robinson, 2007). Traditional evaluations, such as RCTs tend to focus on quantitative outcomes such as gait speed and motor scores, whilst overlooking qualitative feedback and user experience (Vaughan-Graham et al., 2020). Another scoping review into hand exoskeleton systems found that only 38 out of 124 papers reported any human subject assessments, and even those were mostly technical performance tests rather than in-depth user feedback (Süner-Pla-Cerdà et al., 2024).

These omissions of a user's feedback and perspective can limit the interpretation of trial results and a technology's impact, as acknowledged by researchers who cite the lack of qualitative evaluation as a key limitation hindering real-world insight (Delvallée et al., 2024). Without qualitative data, trials only allow for the quantification of outcomes whilst missing why a device succeeds or fails in practice (Sartor et al., 2021). This concentration on impairment metrics rather than the functional needs of individuals has been noted as a reason for a lack of adoption of stroke rehabilitation technologies within the NHS (Kerr et al., 2018).

The implications of overlooking qualitative input and user-centred design (UCD) are important as devices that are designed in a vacuum often suffer from poor usability and low adoption, even if their clinical efficacy appears promising on paper (Peters et al., 2024). In the context of mobile health (mHealth) applications, which refers to medical and public health practice supported by mobile devices (Adibi, 2015), researchers have noted a lack of UCD is a common limitation with many stroke apps require high literacy or tech-savviness to navigate, reflecting designs that did not adequately consider the actual user population (Marwaa et al., 2023).

In the context of this literature, it was therefore considered appropriate that the project undertake a thorough co-design process, defined by the active and sustained involvement of end-users throughout development, in the design of its dosage and intensity monitor, to maximise the system's success and impact in both research and clinical applications.

3.3.1. Principles of Co- Design

The principles of co-design share similarities with those of community-based participatory research (CBPR), emphasising collaborative approaches that respect and integrate the knowledge and experience of all stakeholders (Eyles et al., 2016; Thabrew et al., 2018). These core principles can be summarised as 1) collaborative participation and partnership, 2) mutual learning and empowerment, 3) collective creativity and innovation, 4) systems development and sustainability, and 5) contextual and community-centred:

- There is active collaboration occurring between researchers, designers, developers, and end-users, who are viewed as 'experts of their own experiences.' Stakeholders work collectively throughout the design process.
- There is co-learning with reciprocal exchanges of information, empowering stakeholders through shared decision-making and equal involvement at every stage.
- Creativity is fostered through collective input from all stakeholders, generating innovative solutions tailored to community strengths and needs.
- The design process aims for sustainable interventions, building on existing community strengths and resources to ensure long-term success and integration.
- Recognition is given to communities as social and cultural environments, not just physical settings, requiring a long-term commitment from all involved partners.

The practical implementation of these principles can, however, vary, as there are no universally standardised guidelines for co-design processes (Constantin et al., 2022). These co-design

principles are particularly appropriate for developing the dosage and intensity monitoring system as they ensure the device will directly address the specific rehabilitation needs, preferences, and practical realities of stroke survivors.

By actively involving end-users in each design phase, the intervention can be tailored to enhance user acceptance, functionality, and long-term adherence. Additionally, the principle of mutual learning can enable ongoing refinement based on stakeholder feedback and adopting a user-centred approach that can enhance both usability and practicality.

Finally, emphasising sustainability and contextual appropriateness can also ensure that the dosage and intensity monitoring system can be smoothly integrated into existing clinical and research rehabilitation settings, and improve the likelihood of its' successful implementation and meaningful rehabilitation measurements.

3.3.2. Benefits and Limitations of Co-Design

The key benefit of the co-design process is the enhanced usability of rehabilitation technologies. Involving stroke survivors in design leads to products that are fit for purpose and aligned with users' abilities and needs with an emphasis on accessibility and ergonomics (Wittink et al., 2024). For example, iterative user testing in the co-design of an exercise app interface identified and resolved numerous usability issues, resulting in improved user satisfaction and a 100% task completion rate by the final iteration (Young et al., 2023). Furthermore, co-design approaches often foster higher patient engagement and adherence to rehabilitation programmes as the interventions developed better align with patients' goals and daily realities, making users more motivated to use them consistently (Thal et al., 2025). Participants often report feeling valued and heard through this collaborative design process (Marwaa et al., 2023). Secondary benefits include smoother implementation and improved clinical outcomes, as interventions informed by user insights fit more seamlessly into clinical

routines and participants' lives, enhancing overall uptake and effectiveness (Marwaa et al., 2023).

A scoping review in 2024 did, however, identify key limitations in co-design practices for stroke intervention development, categorising these into recruitment-related, participant-engagement, contextual and logistical, and ethical issues (Singh et al., 2024).

Researchers have reported difficulty in recruiting stakeholder participants for reasons including participant burden associated with high time commitments for activities, limited technological access for participation (particularly relevant during the COVID-19 pandemic), and the considerable resource demands required to accommodate varied participant needs.

In terms of participant engagement, they found disparities in levels of knowledge about the study topic, cognitive and/or communication impairments that required additional time and resources to confirm that participants understood the activities and verified that researchers accurately understood the information shared by participants.

For contextual and logistical limitations, it was found that time and funding constraints limited the iterative co-design process, as additional workshops, meetings, prototypes, or evaluations for further data collection could not occur without additional resources and time, which prevented the optimal stroke intervention from being created to meet the needs and priorities of participants.

Finally, ethical considerations presented challenges, particularly in obtaining informed consent from participants experiencing cognitive or communicative impairments due to stroke, and in managing the risk of participant burden from extended involvement in the co-design process.

3.3.3. The Co-Design Process

Co-design can be defined as involving target users directly in the system design process, actively contributing their knowledge, generating ideas, and developing concepts, which ensures the resultant system aligns closely with user needs and expectations (Noorbergen et al., 2021). General co-design processes are often structured using frameworks that provide a conceptual structure and a shared frame of reference. One widely recognised framework is by Sanders and Stappers, which breaks down the co-design process into four interconnected phases: 1) predesign phase, 2) generative phase, 3) evaluative phase, and 4) post-design phase (Figure 4) (Sanders & and Stappers, 2008, 2014).

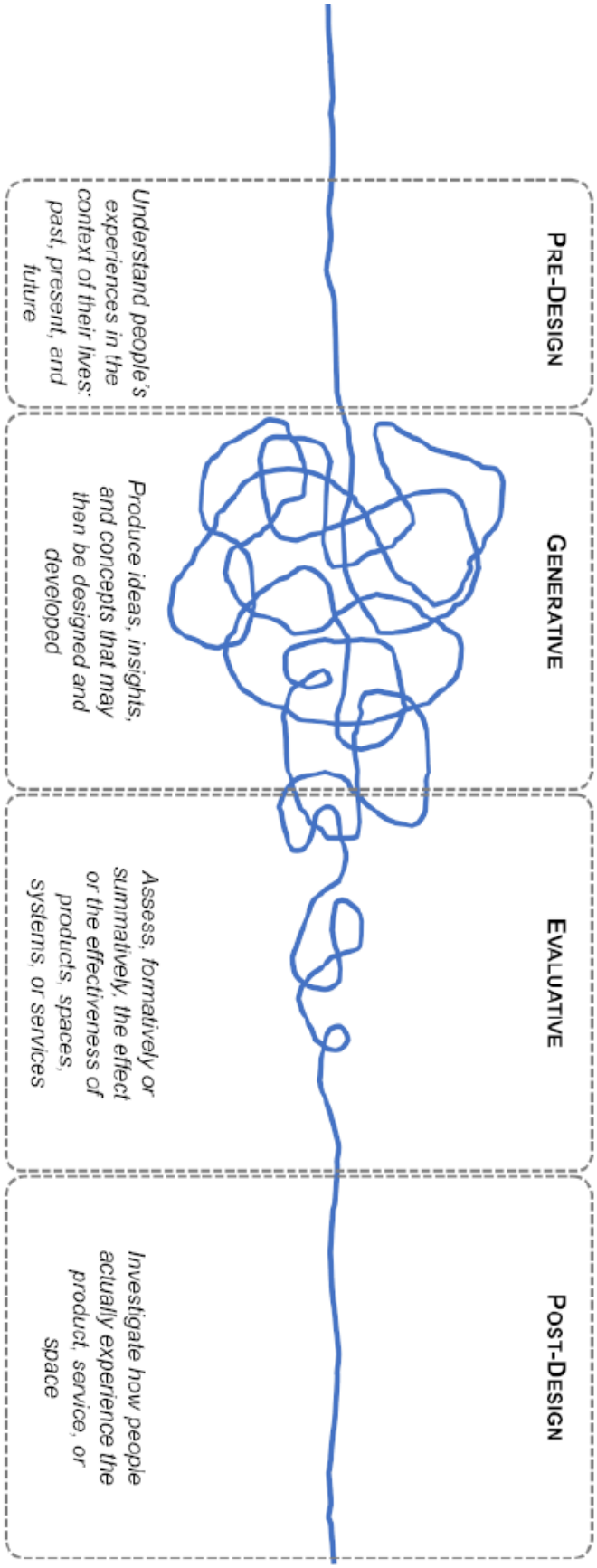


Figure 4 Co-design framework (Noorbergen et al., 2021).

In the predesign phase, the primary goal is to understand the context of use, explore user experiences, set clear objectives for desired outcomes, and inform participants to the relevant issues and opportunities. The generative phase actively engages users in producing original ideas, insights, and concepts, typically through the creation of prototypes such as mock-ups or storyboards. During the evaluative phase, these conceptual designs undergo rigorous assessment by users, enabling critical feedback on usability and effectiveness. Finally, the post-design phase acknowledges the ongoing evolution of the system after implementation, guided by real-world usage data, user feedback, and changing needs, ensuring the system remains relevant and effective over time.

Designing and developing telerehabilitation systems presents unique challenges due to the inherently complex healthcare environment, which requires collaboration among diverse stakeholders including end-users, healthcare professionals, government bodies, and software developers (Noorbergen et al., 2021). The identification and early involvement of these stakeholders, alongside careful planning, communication, and scheduling, are critical yet demanding tasks. Furthermore, telerehabilitation solutions must navigate intricate healthcare processes, policies, privacy regulations, and ethical considerations due to their direct implications for people's health (Noorbergen et al., 2021). Issues around consent, confidentiality, and appropriate usage of data collected via digital telerehabilitation tools also remain largely unresolved, raising unique ethical dilemmas given the blurred lines between research, monitoring, and clinical intervention (Marzano et al., 2015). Additionally, many commercially available telerehabilitation apps lack rigorous standardised testing and theoretical grounding in behaviour change, leaving clinicians uncertain about recommending their use. Evaluation typically falls behind rapid technological development, creating gaps in evidence regarding efficacy, acceptability, and long-term engagement (Burke et al., 2015).

To address these complexities, a recent contextualised co-design framework has been adapted from the established Sanders and Stappers model. This contextualised co-design framework integrates considerations which can help to address these digital telerehabilitation development limitations (Figure 5) (Noorbergen et al., 2021).

Firstly, a dedicated prototyping phase has been added before the evaluative phase which distinguishes the creation of initial simple concepts from testing more advanced prototypes like hardware and software which can optimise the creation of a fully functional version available for rigorous evaluation. Secondly, a dedicated implementation phase follows the evaluative phase, distinct from feasibility testing and focuses on the wider rollout and integration of the digital telerehabilitation systems within its complex healthcare environment, considering aspects such as documentation, training, and the participation of key stakeholders. Lastly, there is now a strong emphasis on immersion throughout the predesign, evaluative, implementation, and post-design phases to understanding the real-world contexts. Deep immersion is vital for clearly understanding the real-world context, identifying relevant stakeholders, accurately grasping their needs and challenges, and ensuring the system effectively addresses identified problems and design criteria.

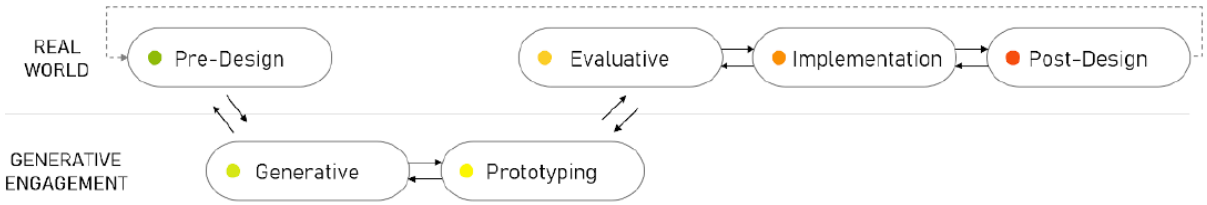


Figure 5 Co-design framework for digital telerehabilitation applications (Noorbergen et al., 2021).

Throughout these phases, particularly in the digital telerehabilitation context, the co-design process is guided by specific considerations or "best practices" that address its complexities. These guidelines interact with and support activities within the different phases of the co-design process.

3.3.4. Guidelines for Meaningful Co-Design

With the core idea of the system leaning towards digital telerehabilitation, it was also appropriate to consider recent proposed guidelines for using co-design methodologies in digital telerehabilitation system development to ensure that the system was developed to a meaningful standard (Noorbergen et al., 2021) (Figure 6). These guidelines are:

- Understanding stakeholder vulnerabilities and diversity
- Planning for and assessing health behaviour changes
- Identifying and involving co-design facilitators
- Immersion into the digital telerehabilitation ecosystem
- Identifying and involving post-design advocates
- Applying health-specific evaluation criteria
- Collecting and analysing usage data to understand impact

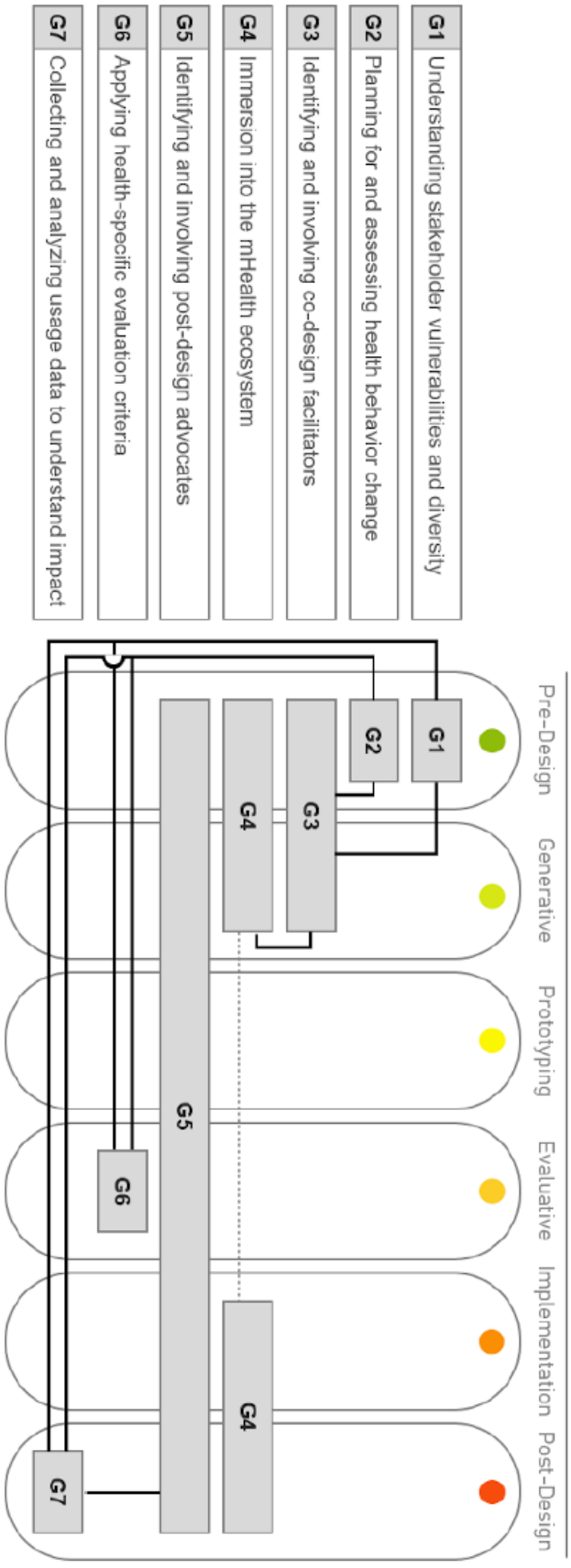


Figure 6 Guidelines in conjunction with codesign phases (Noorbergen et al., 2021).

Effective co-design begins by understanding stakeholder diversity and vulnerabilities to build trust, which is essential when planning for targeted health behaviour changes with input from AHPs. This requires developers to immerse themselves in the telerehabilitation ecosystem, engaging directly with users in their real-world settings to identify pain points and build collaborative relationships. Throughout this process, it is vital to identify post-design advocates who can champion the system's future implementation and rollout. As the system develops, it must be assessed using rigorous, health-specific evaluation criteria and real-world feasibility trials to ensure safety and effectiveness. Finally, after implementation, the cycle continues by collecting and analysing both quantitative usage data and qualitative feedback to understand the system's real-world impact and guide ongoing updates.

To guide the DAIM system's development in line with the MRC framework, we adopted this contextualised co-design framework. This approach was particularly suitable because it enhances traditional methods by adding dedicated prototyping and implementation phases and emphasising real-world immersion. Its structured nature, therefore, provided a clear roadmap for planning all stakeholder engagement and design activities.

Furthermore, given the positive participant feedback reported in the final study of this project (Chapter 7), it can be concluded that the co-design process, combined effectively with the MRC framework, was implemented successfully and contributed meaningfully to the development of the DAIM system.

3.4. The Feasibility and Co-design of a DAIM to support stroke self-rehabilitation

The main aim of the study was to gather perspectives from individuals who have experienced a stroke, contributing to the development of a dosage and intensity monitor. In the completion of this aim this would result in the development of a set of design criteria that align with the MRC framework for complex interventions by adopting a co-design methodology.

3.4.1. Methods

3.4.1.1. Research Settings and Access

The focus groups were held online via the conferencing software Zoom (Zoom Communications, 2025). This platform was recommended by AHPs to maximise accessibility for stroke participants, particularly for those with visual, cognitive, or communicative impairments. Zoom allowed clear presentation of visual materials and questions, supported automatic transcription for effective data management, provided polling functionalities, and facilitated recording of participant audio and video responses.

Considering this, participants were required to have access to suitable technology (e.g., a smartphone, tablet, or computer) and basic familiarity with online communication platforms. Participants were allowed support from carers or family members.

Conducting co-design virtually offered distinct advantages, such as minimising travel requirements, reducing participant burden, and overcoming geographical constraints (Kennedy et al., 2021; Osborne et al., 2022; Singh et al., 2024). Virtual settings, however, introduce challenges, particularly regarding participant digital literacy, reliable internet access, and cognitive or communicative impairments (Anglade et al., 2022). Additionally, ethical

considerations related to informed consent and data validity can be heightened in a virtual environment.

To mitigate ethical concerns, participants received a Participant Information Sheet (PIS) electronically (PDF via email and a secure online OneDrive link (Microsoft Office, 2024)) and were offered physical copies upon request. Participants were advised to join the focus groups from private, quiet locations, and the researchers similarly ensured a confidential environment by conducting sessions privately and in a quiet location. All focus group discussions were recorded, transcribed verbatim, and subsequently anonymised by excluding personal identifiers. The original audio and video recordings were permanently deleted post-transcription. Participants who previously participated in related studies were identified by their previously assigned participant numbers, whilst new participants were assigned unique identifiers. Virtual meetings were password-protected, and access details were provided securely on the day of the sessions to protect participant confidentiality.

Recruitment targeted individuals previously involved in stroke rehabilitation research at the Co-Creation Centre of Rehabilitation Technology (CCRT), University of Strathclyde. These participants had previously consented to be contacted for future research and were familiar with the Technology-enriched Rehabilitation Gym (TERG), making their insights particularly valuable (Kerr et al., 2024). Additional recruitment support was provided by Chest Heart and Stroke Scotland (CHSS), through an advertising email sent to the CHSS Research Group. Interested individuals were instructed to contact the chief investigator, who provided them with a PIS through their preferred method (post, email, or OneDrive). After five working days, participants were contacted to address queries and confirm participation.(Kerr et al., 2024). Additional recruitment support was provided by CHSS, through an advertising email sent to the CHSS Research Group. Interested individuals were instructed to contact the chief investigator, who provided them with a PIS through their preferred method (post, email, or

OneDrive). After five working days, participants were contacted to address queries and confirm participation.

Once participants indicated willingness to proceed, consent forms were distributed electronically. Consent was obtained through e-signatures or typed names (if e-signatures were unavailable). Participants were clearly informed that they could withdraw at any time, but data collected prior to withdrawal would still be used in analysis. Upon receiving consent, participants were included in scheduling arrangements for the focus groups.

3.4.1.2. Inclusion & Exclusion Criteria

Inclusion criteria for the participants:

- Over the age of 18
- Have had an ischaemic or haemorrhagic stroke
- Able to communicate in English (oral and written)
- Reside within the Greater Glasgow area
- Discharged from hospital
- Have access to the internet at home
- Have an email address
- Have access to a video conferencing device e.g. a laptop, tablet, or PC with a camera
- Familiar with video conferencing devices e.g. a laptop, tablet, or PC with a camera

Participants were excluded if they:

- Could not provide written, informed consent.
- Could not attend up to three, one hour long, online focus groups
- Were not experienced in using video conferencing software e.g. Zoom, MS teams or Skype

Written informed consent was to be obtained from all participants immediately prior to the first focus group. For those with communication problems, their carers helped the researcher to communicate to explain the consent form to them to ensure that they were happy to participate. The researcher was also available to address any concerns and questions about the study from the participants prior to the start of the study. Participants were informed prior to the commencement of the study, and at the start of every focus group, that they had the right to refuse to answer a question(s) and/or even withdraw from the study without giving a reason.

3.4.1.3. Ethics

This study received ethical approval from the Strathclyde University Ethics Committee under the protocol number UEC22/94 Kerr: Feasibility of a user-centred collaborative mobile application to support home-based rehabilitation of people recovering from Stroke: a focus group study (Appendix 13). All participants provided informed consent prior to their involvement in the study.

3.4.1.4. Preparation for the Focus Groups

Two focus groups were planned and executed as part of the co-design process, each lasting approximately one hour, with an additional 15 minutes allocated for technical issues or communication delays. The sessions were designed to be informal, avoiding predefined terminology, frameworks, or clinical jargon to support open dialogue and provoke genuine insights from the participants (Figure 7).

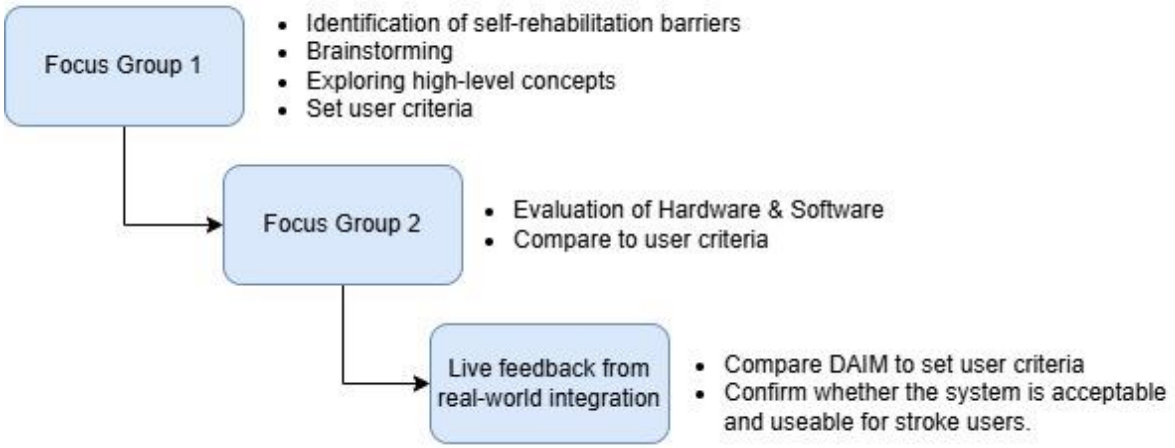


Figure 7 Flowchart of focus group to real-world implementation pathway

Focus Group One served as the foundational session, aiming to introduce the project's concept and establish shared understanding between the participants and researchers. The session would open with an explanation of the core idea behind the DAIM system and introduced the principles of co-design. Time would be allocated for participants to become familiar with one another, which was particularly important given the collaborative nature of the work.

Participants were then asked to share their typical self-rehabilitation activities, including exercises, digital tools, or assistive technologies they currently used. This discussion was also to highlight the challenges they faced in maintaining physical activity and accessing rehabilitation independently. The group would then review preliminary visual concepts of the hardware and software interface. Feedback was invited on the design, language, and overall usability, particularly with reference to the needs of stroke survivors. The session closed by working collaboratively to define a set of initial design requirements that would guide prototype development, establishing the co-design criteria grounded in participants lived experiences.

Focus Group Two was to be held three months later and brought the same participants back together to review a more advanced version of the DAIM system, which included early-stage "soft" prototypes of the hardware and user interface. The group was presented with proposals

for sensor placement, electronic components, and software logic (e.g., how the system would record and display rehabilitation activity). These concepts were explained in plain language, and care was taken to ensure the descriptions were accessible to all participants.

Participants compared the prototypes to the design requirements they had previously set, offering detailed feedback on the extent to which the revised system reflected their original goals and expectations. Recommendations were also gathered to refine both the physical and digital elements of the system prior to the next stage of development. In addition, Zoom's built-in poll feature was used to anonymously collect quantitative feedback across seven questions grouped under five key design categories: functionality, aesthetics, ergonomics, user experience, and perceived limitations (Figure 8). These polls were particularly valuable for gathering structured input from participants who may have found it challenging to speak up during the live discussion.

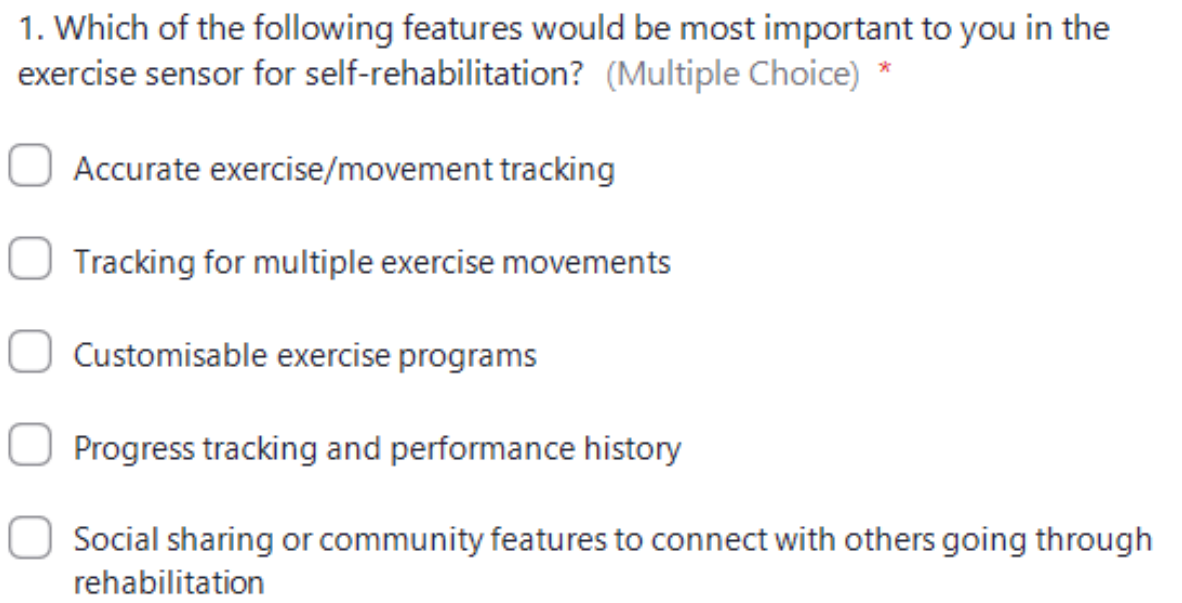


Figure 8 Image of poll layout used.

3.4.1.5. Data Management

The focus groups were video recorded and transcribed verbatim. Any personal information was removed. All findings will be reported back to the participants for an opportunity to confirm that their views had been expressed accurately in the final video conference focus group with the investigators. The resulting pseudo-anonymous data were transferred to a password protected OneDrive (Microsoft Office, 2024) to which only the investigators had access too. All pseudo-anonymised experimental data were coded with unique identification numbers. Upon the study's completion, the identification key linking said numbers to the pseudo-anonymised gathered data was destroyed, making the data anonymous. The resulting data is stored for five years within the same OneDrive password protected folder. Data was to be retained for five years to allow for the analysis and dissemination of research findings through posters or publications.

The poll data from Focus Group Two were automatically recorded and downloaded from the Zoom conferencing platform following the session's conclusion. These results were exported into Microsoft Excel 2016 (Microsoft Office, 2024) format and stored securely in the same password-protected OneDrive folder as the focus group transcripts to ensure consistent data governance. This cloud-based storage was only accessible by the core research team and was compliant with the University's data protection policy. This data was also to be stored for five years.

3.4.1.6. Data Analysis

A thematic analysis approach was adopted, based on the method outlined by Walsh et al., 2024, which involved grouping participant quotes to illustrate common themes and motivations related to self-rehabilitation and self-rehabilitation following hospital discharge for chronic stroke (Walsh et al., 2024). This mixed-methods design combined online focus groups with Braun and Clarke's six-phase thematic analysis (Braun & Clarke, 2006; Walsh et al., 2024),

alongside quantitative questionnaires administered prior to the discussions. Focus groups were conducted via videoconference and guided by a structured interview grid informed by earlier survey findings. Sessions were recorded, transcribed verbatim, and thematically analysed, with questionnaire data integrated to triangulate and enrich the interpretation of emerging themes.

Analysis of focus group ones' audio recordings and the accompanying transcript was conducted by the investigator assigning codes to data found that represented all answers given to the questions posed to the group. After completing this, the codes were collected into groups that reflected similar ideas, and these groups were classed as themes. Any codes which highlighted information irrelevant to the research questions of the focus group were excluded from further grouping. Once complete, all codes and their transcript excerpts were reviewed by a senior member of staff.

Once the poll data from focus group two was stored, the responses were cleaned and organised within Microsoft Excel 2016 (Microsoft Office, 2024), where frequency counts were calculated for each response option. These were then used to generate appropriate visual representations, such as bar charts, and accompanying summary tables. This visualisation allowed for clear interpretation and cross-comparison with qualitative data to identify converging or diverging participant preferences across themes such as functionality, aesthetics, ergonomics, and user experience.

3.4.2. Results

3.4.2.1. Participants

Participants for the two focus groups were recruited from previous stroke rehabilitation studies conducted in the TERG at the University of Strathclyde. Sixteen individuals were considered eligible and invited to participate. Of these, six gave consent to participate in all focus groups with 10 declining; due to other commitments (n=6), uneasiness in using online video

conferencing software (n=3) (thereby not meeting the inclusion criteria) or did not respond (n=1). Between focus groups, the investigating team met to analyse design considerations and review complex design iterations that were not appropriate for a codesign focus group (e.g. hardware circuitry, validation testing, etc).

Of the six focus group participants, two suffered from aphasia resulting in difficulties with their language or speech. Accommodations were made to allow for optimal input during the focus group including the use of the video conferencing chat features and participants were made aware prior that they could have a supportive family member should they require it. All participants were native English speakers. A breakdown of the participant demographics is presented in the table below (Table 6).

Table 6 Focus group participant characteristics

Characteristics	**All Participants (n=6)**
Age (years), mean (SD)	59.0 (8.86)
Gender (male/female)	5/1
Aphasia (aphasic/non-aphasic)	3/3
Time Since Stroke (months), mean (SD)	86.4 (24.74)

3.4.2.2. Identification of Themes

Analysis of focus group 1 resulted in four themes relating to the feasibility and motivations behind the device including (1) Lack of self-rehabilitation indicators after stroke discharge, (2) People are actively seeking sufficient rehabilitation for stroke post-discharge, (3) Peer support acts as a motivator in self-rehabilitation and (4) Reliance on community support to achieve self-rehabilitation. Three defined design criteria and accompanying user requirements included (1) Features to support team motivation, (2) Personalisation prioritisation, and (3) Movement tracking to measure daily rehabilitation activities. All index codes collected contributing to the thematic analysis of the session are presented in Appendix 1.

3.4.2.3. Establishing motivations

Lack of self-rehabilitation indicators after stroke discharge

Half of the focus group (n=3) expressed feeling directionless with the chronic stroke self-rehabilitation advice and dissatisfied with the rehabilitation motivations provided by the NHS on discharge. This dissatisfaction included a lack of communication, an abrupt ending to their rehabilitation programme, and a perceived lack of encouragement and support from their healthcare professionals.

"I see my physio once a fortnight… that's just when I can get her. I've not seen my GP in 2 years" (P3)

"I was just told 'that's the end' when they went away" (P1)

"They keep saying that 'aw you're getting a wee bit better, but you'll never be any better than you are', and that I can't do better. Even if you do have an improvement, they sort of are very quick to knock you back down" (P3)

Analysis of the second half of the focus group's responses found that they remained largely reserved on the matter, with no discernible expressions of opinion or disagreement towards the statements put forth by their peers.

People are actively seeking more rehabilitation for stroke post-discharge

All participants (n=6) stated that they were actively seeking rehabilitation for chronic stroke post-discharge and felt that they required self-rehabilitation after discharge. Participants were using various strategies to manage their recovery, including self-rehabilitation, using devices at home, seeking private physiotherapy, participating in support groups or charities, and experimental research. All participants expressed the need for ongoing rehabilitation and emphasised the importance of motivation in their recovery journey.

"My biggest deficit is still my left arm. I mean I've got no movement below my shoulder in my left arm at all." (P5)

"Well, I don't do anything. I'm basically self-managing as such" (P2)

"I mean I did get some (referring to physiotherapy) when I came out from hospital at first, but it tailed off very quickly, which is why we went for private physio." (P5)

Peer support acts as a motivator in self-rehabilitation

A majority of participants (n=4) outwardly emphasised the importance of social support during self-rehabilitation, with many recognising the value of peer support from individuals who have had similar experiences. They noted that their social needs are often not prioritised in the self-rehabilitation of their stroke and that they find motivation when able to engage socially whilst completing rehabilitation exercises. Additionally, participants highlighted the need for more social options during self-rehabilitation and felt that being surrounded by others who have experienced a stroke provided valuable support.

"Being part of something, that's the social aspect of your app. Any kind of interaction. It's really positive." (P2)

"Because I'm by myself, I'm bored sometimes. I need something else; it would be better for me" (P6)

Reliance on family & friend support to achieve self-rehabilitation

A third of participants (n=2) mentioned relying on the support of family or friends to achieve their daily self-rehabilitation goals. When this support was limited due to COVID-19 restrictions, participants reported negative impacts on their rehabilitation progress. As a result, participants emphasised the need for supplementary self-rehabilitation options that could provide social connectivity in the absence of family support. The development of such options

may help improve rehabilitation outcomes, especially during times when in-person support is not feasible.

"But I get it from my friends. She comes in Monday, Tuesday and Wednesday, the rest I have got to do myself, but it's okay, better than nothing." (P1)

"The problem is with the virus. We didn't do it. So those are problems, I had 2 years where I did nothing, and now I have to do it again." (P6)

3.4.2.4. Identifying design considerations

The DAIM comprises three components: an intensity-tracking sensor, a dosage-tracking sensor and a mobile application that visualises the collected data and provides social connectivity. Before conducting the focus groups, the researcher identified the core components of the intervention and determined their feasibility within an achievable timeframe under the MRC framework.

Participants were provided with a general overview of the initial intervention idea and were asked to brainstorm design considerations and challenges that currently impacted their daily rehabilitation. Using discussion prompts, participants suggested how they would like to use the mobile application, features they felt would motivate them to complete daily rehabilitation tasks and design considerations surrounding how the hardware would be utilised in real-world situations. This feedback was used to develop the user requirements and design considerations of the intervention (Section 3.4.3).

User Interface (UI) Co-design considerations

A majority of participants (n=5) outwardly expressed a desire for their self-rehabilitation progression to be tracked as a group, with each user contributing to an overall group task, enabling them to "check in" with each other and rely on the contribution of all participants to see overall visual feedback from the mobile application.

"Yeah, I think the app might benefit from kind of group thing or somewhere where you can, you know, just clock in with other people, because it would be, you know, affirming, yeah. That's very important." (P2)

To meet this need, the UI of the mobile application should include features that support group motivation and progress tracking. Users valued the ability to track their self-rehabilitation progress, receive encouraging feedback, and work towards shared daily goals with others. The implementation of these features can promote user engagement and satisfaction with the application, thereby improving the available support and access to stroke rehabilitation.

User Experience (UX) Co-design considerations

Participants expressed that previous rehabilitation experiences with their physiotherapists were individually tailored to them and would therefore like to see this reflected in the device UX design.

"When I'm working with my physio, we tend to so try and focus on things we want to achieve because it allows me to do things. So the moment we're just starting to do a wee bit walking without a stick as a goal, being able to go through to the kitchen, make myself a cup of coffee, and then walk back with it, to my seat. It is functionality… It's quite personalised… If you could make the app work like that" (P5)

To meet this need, the device should prioritise personalisation. Including this feature that caters to individual user needs and goals can improve user engagement, satisfaction, and health outcomes.

Hardware Co-design considerations

The hardware aspect of the device is aimed to measure the dosage and intensity of rehabilitation activity the user partakes in and so the intensity tracker may require the user to physically place

a sensor on themselves to maximise accurate measurements. As the target user is currently self-managing chronic stroke, it is important to identify the usability requirements to ensure that the device can be used optimally.

All participants (n=6) agreed that they would like a form of tracking of their physical progress and that a wearable sensor would achieve this.

"I think that'd be really good thing, and that, like anything that goes around the wrist and the leg that can the track movement and anything that can encourage that, even if it doesn't really do you know as much, the fact as you're trying to do, because you know, you're trying to engage with it. It'd be good." (P2)

To meet the standards presented to the researcher, the device's hardware should prioritise ease of use and compatibility with common devices, which can increase user satisfaction and adoption. It was identified that the accuracy of movement tracking was not prioritised by participants; rather, they preferred a visual representation of general movement progression in the device's UI.

3.4.2.5. Polling Results

The second focus group aimed to refine and validate the initial design priorities established during the first focus group by presenting a more developed concept along with early-stage software prototypes. This session served as a bridge between the initial idea generation and the upcoming phase of physical prototype development. An anonymous polling feature was used as an additional method to support participants who may not have felt comfortable speaking out due to confidence or communication difficulties. Poll questions were organised into five key themes which aligned with the core design considerations: functionality, aesthetics, ergonomics, user experience and limitations.

Functionality

Figure 9 shows the participants preferences regarding the desired features of the DAIM system (n=6, with multiple selections of answers allowed). The most frequently selected features were "progress tracking and performance history" and "tracking for multiple exercise movements". "Accurate exercise/movement tracking" and "customisable exercise programme" each received two selections, whereas social or community features were least prioritised.

Participants rated the importance of the DAIM system evoking positive emotional engagement on a 6-point scale ranging from "Extremely Important" to "Not at all Important". Half of the participants considered it "somewhat important" (n=3), one participant viewed it as "extremely important", while two participants deemed it "not at all "important".

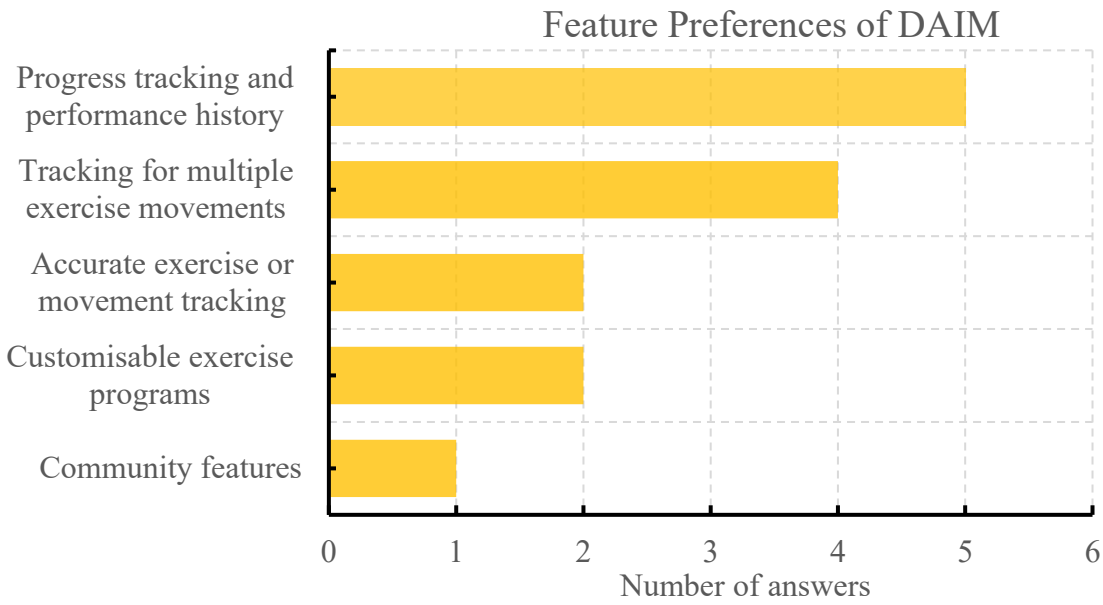


Figure 9 Horizontal bar chart of participant feature preferences for the DAIM (n=6, multiple selections allowed).

Aesthetics

Participants' aesthetic preferences for the DAIM are presented in Figure 10. "Customisable covers or bands" was most preferred, followed by "subtle and neutral tones". "Sleek and minimalist design" was chosen by one participant.

The importance placed on aesthetics for maintaining engagement was evenly divided across participants, again using a 6-point scale, with two participants each rating it as “extremely important”, “somewhat important”, and “neutral”.

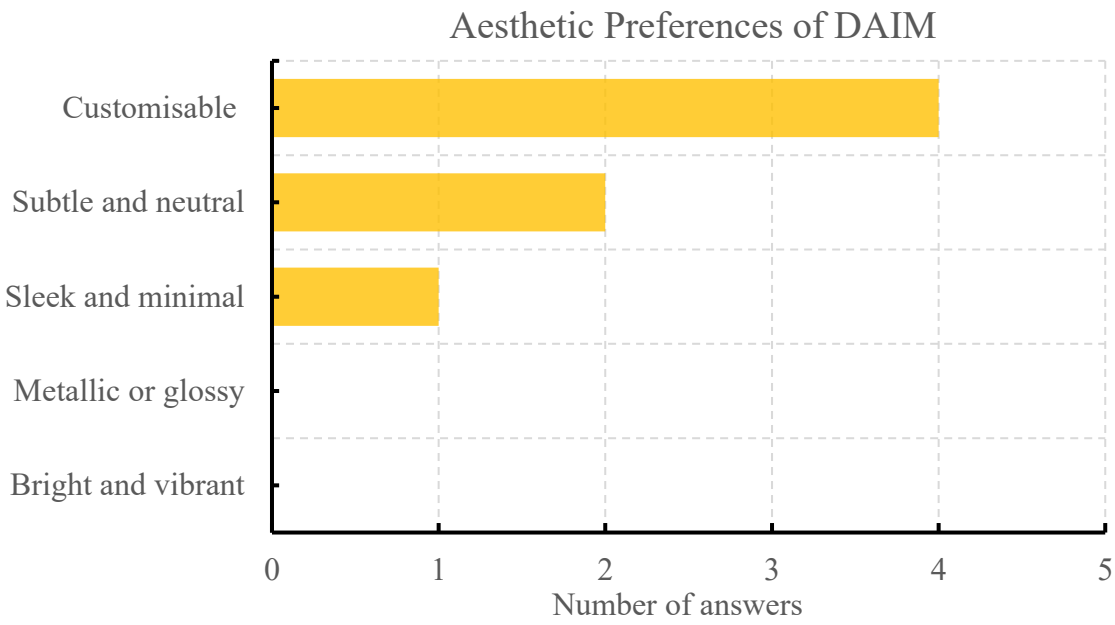


Figure 10 Horizontal bar chart of participant aesthetic preferences for the DAIM (n=6, multiple selections allowed).

Ergonomics

All participants (n=6) consistently preferred using a strap or band around the affected limb as opposed to a “Clip or attachment to clothing” or “Device placed in pocket”.

User Experience

Preferences for the type of feedback participants considered most helpful whilst using the DAIM are presented in Figure 11. Visual feedback was most popular, followed by auditory cues. Only one participant preferred vibration or haptic feedback.

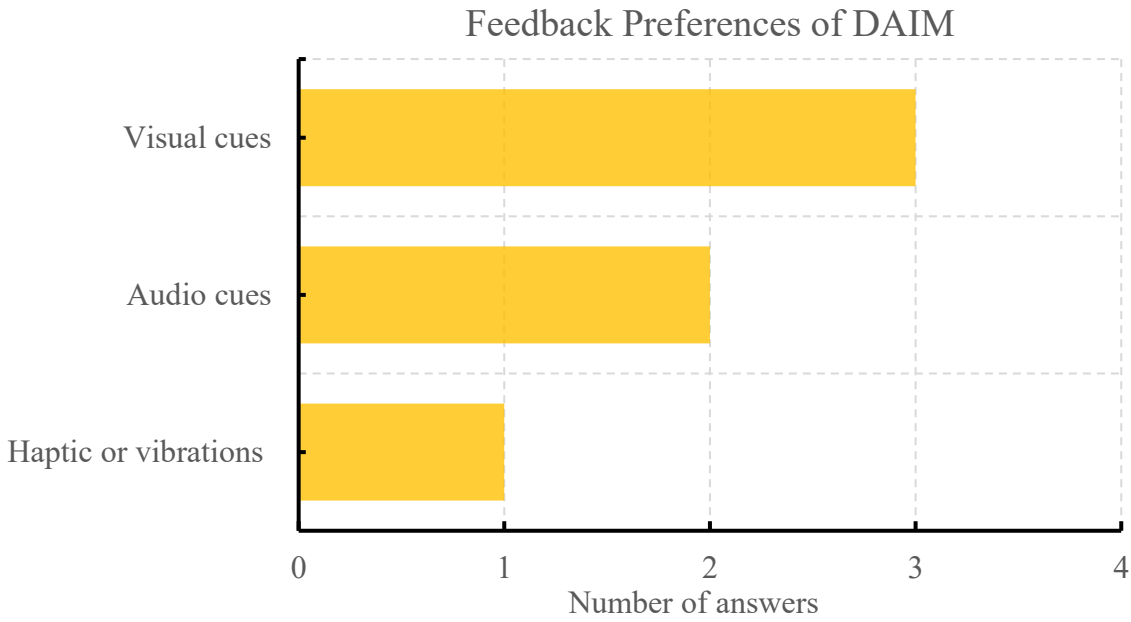


Figure 11 Horizontal bar chart of participant feedback preferences for the DAIM (n=6, multiple selections allowed).

Limitations

Participant concerns regarding potential limitations of the DAIM system are illustrated in Figure 12. The main concerns were equally distributed between "understanding and interpreting data" and "positioning difficulties". Concerns about battery life or charging issues were less prominent but was highlighted by one participant. There were no perceived concerns about lack of personalised features, accuracy concerns or any other suggested potential issues.

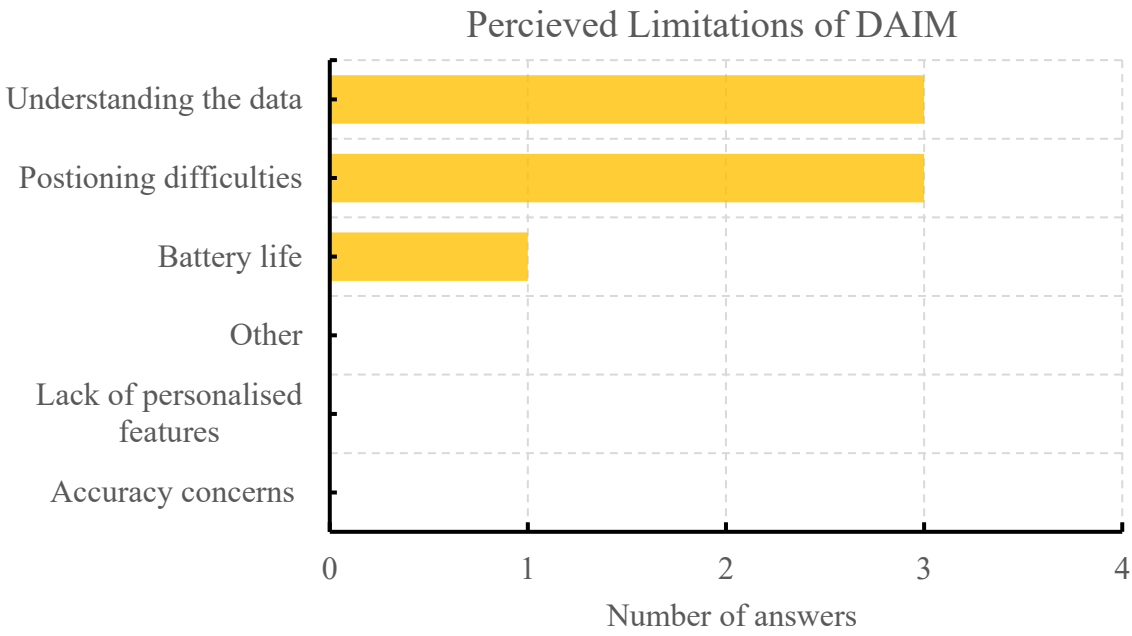


Figure 12 Horizontal bar chart of perceived limitations for the DAIM (n=6, multiple selections allowed).

3.4.3. Discussion

In medical device and intervention development under an MRC framework, a co-design methodology can be particularly useful in designing digital telerehabilitation devices to aid in supporting motor function and mobility rehabilitation (McKinney et al., 2020; Olafsdottir et al., 2020; Santin et al., 2019). By involving people with chronic stroke and other stakeholders

in the design process, researchers can gain insights into the unique challenges and opportunities that different users face, leading to the development of more tailored and effective rehabilitation devices. The co-design approach can also facilitate ongoing feedback from users to refine device design and functionality in response to changes in patient needs.

Whilst thematic analysis looks at direct quotes, this focus group study involved participants who all had a stroke, and some were aphasic (n=2). As a result, there were times when a participant would simply nod their head in agreement or give a gesture that was non-translatable to the written word. This poses a challenge for capturing all relevant insights and nuances from the participants, especially those who may struggle with verbal communication. To address this, nonverbal observation was incorporated to determine the final number of participants contributing to a discussion. Additionally, general agreement in the form of a simple 'Yes' or similar was treated as an expert that could be assigned to a code or theme. This ensures all participants have an equal opportunity to express their thoughts and opinions.

Peer support and collaboration during chronic stroke self-rehabilitation was highlighted by the participants as a substantial gap in their current situation (Table 7). Current research highlights the importance of peer support within the self-rehabilitation of stroke, with researchers highlighting the need for future self-rehabilitation interventions to maximise peer support in their design considerations, this is also followed by incorporating techniques which support knowledge development, goal setting and access to resources (Clark et al., 2020). The participants and current research suggest that peer support allows a user to facilitate the sharing of rehabilitation information and provide support to one another which overall increases self-rehabilitation motivation. It is important to consider however, the views and collaborative approach of healthcare professionals for the effective implementation of a group rehabilitative intervention (Corbin et al., 2023). Both focus groups were mediated by an experienced physiotherapist who also provided feedback about the device throughout the sessions, in

addition to this initial and soft-protypes and concepts were then presented to another physiotherapist and occupational therapist for further comment.

Current peer support available to stroke individuals comes in the form of stroke support groups run by various charities, therefore it was found that whilst most of the participants did have access to, and participated in said support groups, they felt that it was not accessible regularly enough to achieve their daily rehabilitation goals due to lack of resources or weekly daily availabilities.

The findings of this study align with user-centred priorities previously identified in literature. Participants noted the importance of ease of use and simplicity in the technology, particularly in relation to wearable sensors and movement tracking. This echoes Kerr et al.'s findings that ease of use, evidence of effectiveness, access, and user training are among the top stakeholder priorities for rehabilitation technologies (Broderick et al., 2023; Kerr et al., 2018). The participants also emphasised that accurate sensor placement was less important than having a clear visual representation of their rehabilitation progress, which support the conclusion that usability and understandability were more important than technical precision.

Participants also prioritised the value of personalisation and goal-oriented rehabilitation, for example tailoring exercises to individual functional goals and daily routines. This aligns with Van Ommeren et al.'s systematic review, which identified usability, practical applicability, and positive user attitudes as critical factors in technology adoption post-stroke (van Ommeren et al., 2018). Similarly, the participants' desire for social features including group progress tracking and social motivation, highlights that sustained engagement depends on meaningful integration into daily practice and the perceived benefit of the technology, rather than simply adding advanced features (Ambros-Antemate et al., 2023).

Collectively, these results indicate that successful stroke rehabilitation technologies must balance therapeutic effectiveness with user-centred design, and prioritise usability, personalisation, social support, and motivational feedback.

3.4.3.1. Resulting Requirements and Concept Development

A key strength of this study was the active engagement of participants using a co-design process, which directly informed the design of the DAIM system. As defined previously this co-design approach meant that the problem itself (creating a dosage and intensity monitor for self-rehabilitation from Section 3.3. Co-design) was already predetermined based off the results of the literature review (Chapter 2, Section 2.6.1. Objectives). However, the focus group would act as a method to directly involve the end-users in how the functional and experiential aspects would work, this could then be systematically analysed and translated into design requirements. For example, participants noted the importance of progress tracking and visual feedback to maintain motivation during self-rehabilitation. This directly informed the researcher to develop a "Progress Tower" gamification feature via a mobile application, allowing users to see both their individual and group achievements (3.4.2.4. Identifying design considerations).

The inclusion of a mobile application in the DAIM system was directly informed by participants' prioritisation of personalised rehabilitation exercises tailored to their functional goals and daily routines. Polling results reinforced this need, with a majority of participants choosing "customisable exercise programme" as a key priority (Section 3.4.2.5 Polling Results). In addition, participants highlighted the importance of accessible, real-time feedback and the ability to monitor both individual and group progress (Section 3.4.2.4, Identifying design considerations). This preference was further supported by polling, where "progress tracking and performance history" and "tracking for multiple exercise movements" were the most frequently selected features (Figure 10). The mobile application therefore provides a

flexible platform for delivering rehabilitation data in an understandable and motivating format, so that users can track daily goals, visualise long-term progress, and participate in peer-supported rehabilitation, all of which were prioritised by the participants.

Another clear recommendation from participants was the need for wearable and easy-to-use hardware. All participants preferred a strap or band placed on the affected limb over alternative options such as clips or pocket devices. This directly led to the selection of a thigh-worn sensor design, ensuring accessibility and ease of use, especially for individuals with limited dexterity post-stroke (Section 3.4.2.4, Identifying design considerations). Participants also indicated that precise measurement was less important than providing clear and understandable feedback. Consequently, the hardware design prioritises user-friendly alignment indicators and intuitive visual outputs rather than overly complex sensor accuracy.

The importance of peer and community support was consistently raised across the focus groups. Participants described feelings of isolation and the motivational benefits of interacting with others completing similar rehabilitation tasks. In response, the DAIM system includes a group progress tracking social feature, allowing users to contribute to shared goals and visual feedback (Section 3.4.2.4, Identifying design considerations).

Finally, gamification elements, such as animated progress feedback, points, and achievement indicators, were incorporated following participants' expressed need for features that sustain long-term engagement. This aligns with the co-design findings that participants valued interactive and rewarding elements that transform repetitive exercises into more motivating and visually engaging experiences.

The co-designed intervention led to the concept development of the DAIM system, a system that integrates a wearable sensor, an external dosage tracker and a mobile application. The system was shaped through an iterative, co- design process that emphasised daily rehabilitation

goal setting, real-time feedback, and peer support. Participants envisioned a solution that could support self-managed rehabilitation in both home and research settings, including environments like the gym or the TERG.

The co-design process also defined the hardware approach. To simplify tracking and ensure accessibility, Near-Field Communication (NFC) was selected for the dosage component. NFC readers could be easily placed at rehabilitation stations to allow users to log activities by tapping personalised NFC tags, a method especially suitable for individuals with limited dexterity or cognitive challenges. By also providing end-users with a wearable sensor, this can enable automatic tracking of various recognised rehabilitation tasks, while an app allows users to manually log additional, less structured activities (e.g., household tasks like doing the dishes).

Each user can receive daily rehabilitation goals, and when completed, their progress contributes to a group-based visual feedback mechanism, promoting peer motivation and collective accountability. This feature, represented by a collaborative "Progress Tower," was well received in concept and supports the integration of community dynamics into self-rehabilitation (Figure 13, Figure 14). Historical data and goal progression are also stored within the app, allowing users to monitor their long-term progress and optionally share this information with healthcare professionals.

The second focus group validated and extended the insights from the first, particularly through polling that quantitatively highlighted user preferences. Participants strongly prioritised functionality features such as progress tracking, support for multiple exercise modalities, and customisable programmes. These insights directly informed design decisions such as incorporating a modular interface to support various motor rehabilitative exercises. Preferences

for visual and auditory real-time feedback led to the implementation of multi-sensory cues across both the app and hardware components.

Aesthetic preferences leaned toward customisable or subtle design elements, supporting the decision to create a device that is discrete and adaptable to user tastes. Ergonomic feedback showed unanimous support for a strap or band worn around the affected limb. Moreover, preferences for visual and auditory feedback in real-time informed the implementation of multi-sensory prompts in both the hardware and mobile application. The polling responses around limitations found that most concern was about interpreting data and device positioning, this highlighted the need for a user-friendly interface and clear identifications on the band for consistent device alignment.

Three key user requirements consistently emerged throughout both focus groups: (1) the need for gamification to sustain engagement, (2) personalised self-rehabilitation guidance, and (3) features to foster community and peer support. Gamification, defined as "the integration of game elements into non-game environments," including features such as points, badges, leaderboards, and instant feedback (Rodrigues et al., 2019; Sánchez-Gil et al., 2025), was highlighted as crucial for sustaining user motivation. In response, the application integrated visual elements such as animated progress frames during exercises, providing real-time visual feedback that simulates progression toward trophies or achievements. Additionally, clearly visible progress bars with completion indicators were incorporated to reinforce users' sense of achievement upon completing daily rehabilitation tasks. To enhance individualisation, the app would match rehabilitation goals to the user’s self-reported experience and stamina level. This tailoring could help to mitigate fatigue, increase relevance, and sustain long-term usage.

These user-driven insights culminated in the generation of a comprehensive design requirements table (Table 7) that shaped both the technical and experiential dimensions of the

DAIM system. All features were designed to align with both the clinical engineering constraints of the research team and the real-world needs of the end users.

Table 7 Design criteria developed from co-design focus group. The design criteria were identified based on the input and feedback provided by the focus group participants

Design Requirements	Description	Priority
Self-rehabilitation advice and rehabilitation motivation	The intervention should provide clear and effective self-rehabilitation indicators for users to prevent them from feeling directionless and dissatisfied.	High
Communication and support	The intervention should promote effective communication and support between healthcare professionals and users to ensure a smooth transition from rehabilitation to self-rehabilitation.	Low
Ongoing rehabilitation	The intervention should facilitate ongoing rehabilitation for chronic stroke patients and provide the necessary tools and strategies to manage their recovery journey.	High
Peer support	The intervention should foster peer support and social connectivity among users to promote motivation and provide valuable support.	High
Family and friend support	The intervention should provide supplementary self-rehabilitation options that can provide social connectivity in the absence of family support.	Medium
Movement tracking sensor	The intervention should include a movement-tracking sensor to track rehabilitation progress and provide visual feedback.	High
Mobile application	The intervention should include a mobile application	High

	that enables stroke patients to track their rehabilitation progress, interact with a community, and access various features that promote motivation.	
Group tracking feature	The mobile application should include a group tracking feature that enables stroke patients to track their self-rehabilitation progress as a group, providing overall visual feedback to promote motivation.	High
Design for ease of use and accessibility for individuals with disabilities	The intervention useability and accessibility should be optimised for individuals with disabilities	Medium

As a direct result of these iterative design workshops and user inputs, Figure 13 was developed as a visual mock-up of the complete DAIM system. This figure illustrates the integration of all critical components identified through the co-design process, including the wearable sensor, the NFC tracking mechanism, and the mobile application interface. It serves both as a conceptual overview and a blueprint for subsequent prototype development, aligning closely with the engineering and user-led design requirements set out in the focus groups.

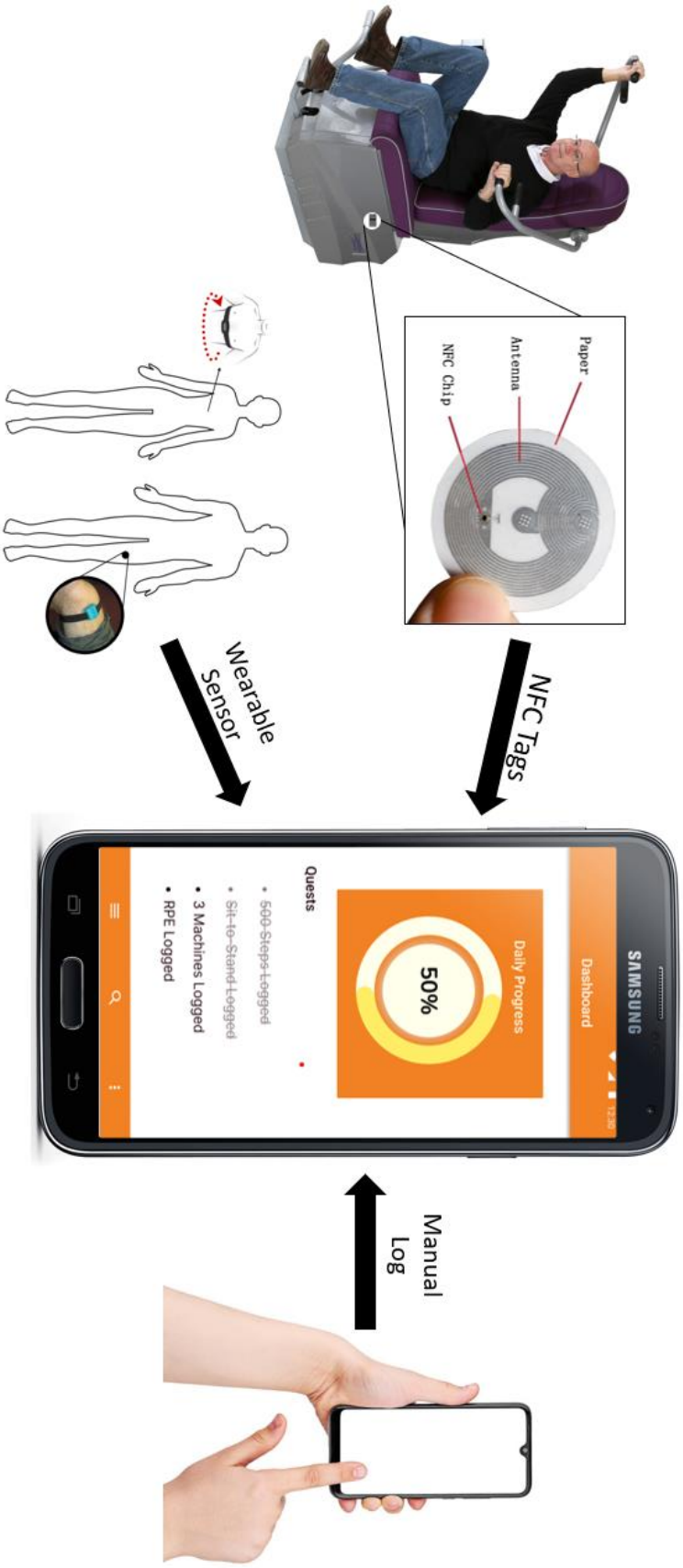


Figure 13 Conceptual intervention design based on co-design focus group criteria.

To further visualise the mobile application's structure and user interface, Figma was used to develop a full mock-up of the DAIM app (Figure 14)(Figma, 2024). Figma is a cloud-based interface design and prototyping tool that allows for real-time editing of user interface elements, making it especially effective for iterative and co- design workflows. Using this platform, a series of screen designs were created to simulate how users would navigate the app, view progress, receive real-time feedback, and engage with group-based rehabilitation features. These sketches were directly informed by the co-design sessions, particularly the prioritised features identified in polling and group discussion. Final Figma sketches would also need to reflect accessibility best practices, including large buttons, simplified navigation, and visual feedback elements tailored for users with cognitive or visual impairments following stroke.

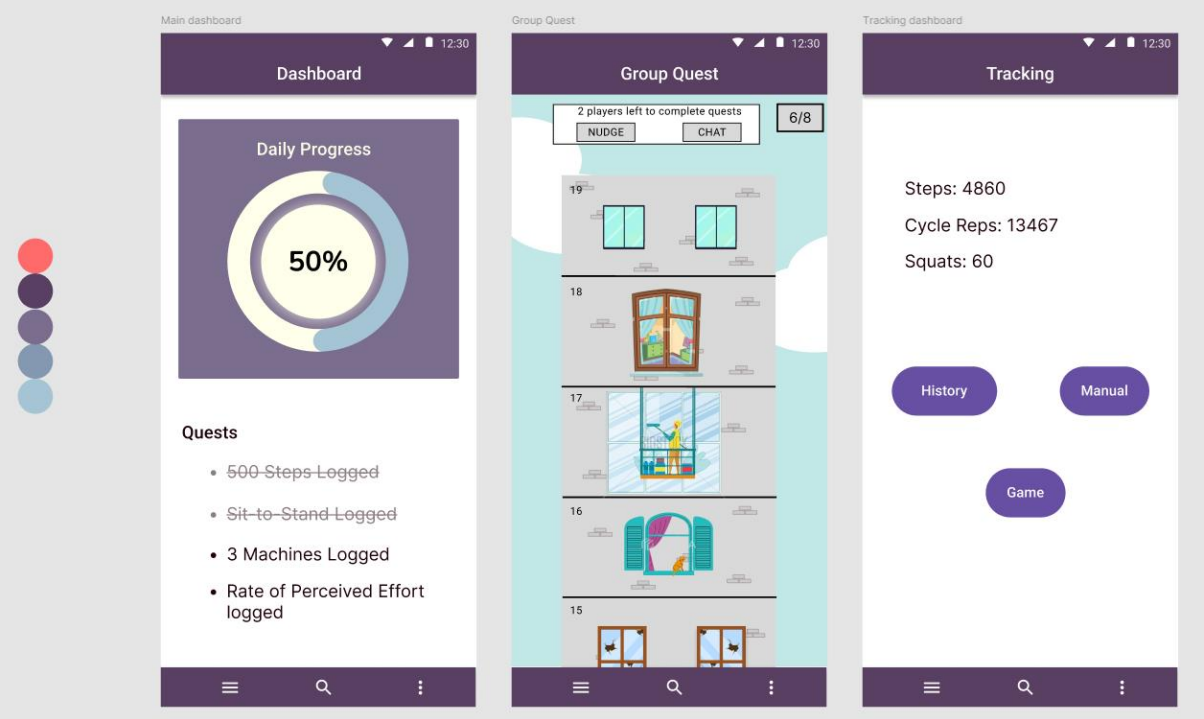


Figure 14 Initial Figma prototype sketches of each page of the proposed app with a proposed colour scheme.

3.4.3.2. Study Limitations and Implications for Future Research

The study's co-design methodology brings clear advantages, notably enhancing user engagement and ensuring the intervention is closely aligned with end-users' rehabilitation needs, key criteria shown to improve uptake and effectiveness in stroke rehabilitation interventions (Noorbergen et al., 2021). There are several limitations; first, the small sample size and limited demographic diversity within the focus groups may have not captured the broader needs of the stroke survivor population. Secondly, participants' prior experiences and preferences may have also shaped their recommendations, potentially biasing the design toward their individual perspectives rather than more generalisable needs. Participants were found to be mostly positive and naturally motivated individuals as seen in their efforts to seek out and actively participate in rehabilitative research, therefore the DAIM may be developed with a slight lean towards that type of target population. To try and mitigate this, feasibility and usability studies should incorporate a larger pool of participants and be tested in real-world settings with minimal interventions from the investigator. Additionally having a large pool of participants throughout the entire co-design process will also contribute to optimising the DAIM for use across all personality and stroke types (Said et al., 2024).

Moreover, although polls offered an anonymous format facilitating input from those less comfortable speaking up, polls offer only a snapshot with limited detail and cannot capture nuanced opinions which can result in response bias (Morgan, 1996). Participants may have selected options they perceived as positive rather than expressing more critical views, especially in group settings. Additionally, the small sample size (n=6) risks non-response and participation bias, further limiting generalisability. After analysing the poll data via Microsoft Excel 2016, it was found that all participants answered all questions.

Despite these limitations, the study provides valuable insights into the benefits of incorporating a codesign methodology and allows for the development of a supportive intervention that

integrates novel concepts aimed at fulfilling the requirements of users, improving effectiveness and significance (Singh et al., 2024). The limitations mentioned can be mitigated through careful planning and execution of the co-design focus group methodology, such as through purposive sampling, the use of skilled facilitators, and the use of structured discussion prompts. Overall, by documenting stakeholder involvement and using mixed-method evaluations, future work can validate whether co-design improves outcomes such as usability, engagement, and clinical efficacy as emphasised by recent frameworks (Peters et al., 2024). By embedding co-design thoughtfully, the DAIM's development sets an example for stroke rehabilitation research, demonstrating how continuous user engagement and rigorous evaluation can improve the development, implementation, and eventual impact of digital health tools.

3.5. Chapter Summary

This chapter adopted a qualitative research methodology, utilising two focus groups to capture diverse stakeholder perspectives and preferences regarding the co-creation of a dosage and intensity monitoring system for stroke rehabilitation. Guided by principles of co-design in compliance with the MRC framework, the system includes an integrated mobile application and accompanying hardware designed to facilitate self-rehabilitation through personalised daily tasks and collaborative group challenges whilst also accurately measuring a user's dosage and intensity of rehabilitation performed. The initial focus group clearly defined the essential design criteria, emphasising peer support, goal setting, and knowledge building to foster motivation and adherence. The second focus group refined these requirements, prioritising specific hardware and software features to enhance usability, engagement, and effectiveness. Moving forward, subsequent project phases and chapters will involve iterative development and evaluation of hardware prototypes, gathering continuous feedback from end-users to

ensure alignment with stakeholder needs and expectations, then a final prototype will undergo a complete pilot study in a research setting.

Chapter 4. Design and Development of Dosage Tracking System

4.1. Introduction

Following selection of the final concept choice (Chapter 3), the next stage, aligned with the 'Development' phase of the MRC framework, involved iterative refinement and prototyping of each core component of the DAIM system: the dosage tracker, intensity tracker, and mobile application. This chapter specifically addresses the design, development, and validation of the digital dosage tracking system. Initially, key design requirements were identified from stakeholder feedback (Section 3.4.3.1) and translated into a practical working prototype through iterative hardware and software development. The dosage tracker was designed to capture the duration and frequency of rehabilitation activities, aligning with the established definition of rehabilitation dosage (Section 2.3.2.1)

Prototype validation began with a pilot study involving healthy participants to assess initial usability and technical performance. Subsequent evaluations extended into real-world rehabilitation contexts: firstly, within a research gym environment (TERG), and subsequently, in a clinical rehabilitation setting involving stroke survivors. Both studies examined the feasibility and validity of the dosage tracker by comparing automated digital logs against manually recorded data. Continuous stakeholder feedback throughout these stages directly informed refinements, shaping the final version of the dosage tracker.

4.2. Prototype Development

The co-design focus groups and follow-up polls (Section 3.4) produced a clear set of co-designed criteria for the dosage-tracking component of DAIM. Participants wanted a system

that could reliably record the exact duration and frequency of each rehabilitation activity, not just a rough estimate, and do so across a variety of exercise modes without the need to re-configure hardware between stations. Users repeatedly ranked simplicity and ease of use as top priorities (Section 3.4.2), insisting that every interaction be “one-step and go,” while simultaneously stressing that clear feedback after each scan was good for reinforcing for confidence and sustained engagement. While the intensity tracker, (Chapter 5), will be implemented as a wearable device tailored to lower-limb rehabilitation due to the complexity of tracking upper-limb motion in real-world environments (Chapter 2), the dosage tracker is designed as an external scanning solution. This makes it well suited to capture a broad range of rehabilitation activities, however there would be no movement metrics to pair with it.

4.2.1. Hardware Components

Rehabilitation dosage can be conceptualised and measured using a range of methods, each with distinct strengths and limitations. Within the rehabilitation literature, objective measurement of dosage has most commonly focused on wearable IMUs. These systems are typically designed to quantify movement-related metrics such as step counts, joint kinematics, or physiological measures including heart rate, rather than explicitly capturing *when* and *for how long* a person engages with a specific rehabilitation activity or workstation (Parnandi et al., 2022; Shin et al., 2020). While wearable sensors can reliably detect that a patient is moving, they cannot inherently determine which rehabilitation device or activity is being used without the implementation of complex activity-recognition algorithms.

By contrast, a station-mounted identification system, such as NFC, enables unambiguous attribution of rehabilitation activity through deliberate physical interaction with a reader affixed to a specific piece of equipment. This approach allows activity identification to be

determined by spatial context rather than inferred from movement patterns, thereby avoiding classification ambiguity that can arise with wearable-only approaches.

With this in mind, alternative non-digital methods of recording rehabilitation dosage, such as manual self-logging, were also considered. However, these approaches also present feasibility limitations within a stroke population. Manual recording requires users to carry a recording tool, track time accurately, and document activity independently. This process thus assumes that the user does not have any cognitive, aphasic or physical impairments, which cannot be assumed in individuals with stroke. Additionally, people are known to overestimate active therapy time, often rounding durations and struggling to distinguish between active exercise and inactive periods such as setup or transitions (Gittins et al., 2020).

Bluetooth Low Energy (BLE) beacons were also evaluated as a potential solution. BLE beacons are small, battery-powered transmitters that broadcast unique identifiers over distances of up to 100m to nearby devices such as smartphones or receivers (Skýpalová et al., 2025). However, the relatively long signal range and ability to penetrate walls introduces substantial ambiguity in determining whether a user is actively engaged with a specific rehabilitation device or merely passing nearby. This may limit the precision of start and stop time detection. Furthermore, deploying sufficient access points to these across different indoor environments may be costly (Ogasawara et al., 2023). Therefore, it was identified that the dosage tracking device would require a reader with a smaller readable range.

In this work, dosage was operationalised primarily through frequency and duration of activity. NFC offers a low-cost, short-range (<10 cm) interaction mechanism that supports flexible form factors, including cards, stickers, and key fobs. This design minimises technical interaction demands on users and reduces overall user burden (Razmi & Babazadeh sangar, 2016). Importantly, the system also aligns with current clinical practice, where rehabilitation dosage

is typically recorded as estimated time spent at a workstation. However, it is acknowledged that NFC-based systems are not without limitations. Practical read-range errors may occur due to tag placement or user behaviour, and missed scans resulting from user forgetfulness may lead to under-recording of activity duration.

Quick Response (QR) codes were also considered as an alternative, as they eliminate the need for dedicated hardware by allowing users to scan a code using a smartphone camera (Chang et al., 2022). While QR codes represent a low-cost solution, they impose interaction requirements that could be incompatible with the stroke population. Scanning a QR code requires opening a mobile application, aligning the camera, and holding the device steady, which may be challenging for individuals with hemiparesis, visual impairments, or reduced coordination (Lemke et al., 2022). Furthermore, reliance on personal smartphones assumes device ownership, sufficient technical proficiency, and accessibility accommodations, which cannot be guaranteed in all users (Burns et al., 2022).

All considered approaches were systematically compared (Table 8) , and NFC was selected as the most appropriate compromise between accuracy, accessibility, user burden, and feasibility within real-world rehabilitation environments.

Table 8 Comparison of dosage tracking techniques

Feature	**NFC (Chosen)**	**Manual Logs**	**Wearable Sensors**	**BLE Beacons**	**QR Codes**
Duration Accuracy	High	Low	Moderate	Low	High
Station Attribution	High	High	Low	Moderate	High
User Interaction	Medium	High	Medium	None	Medium
Accessibility	High	Low	Medium	High	Low
Power Needs	High	None	High	High	None
Cost	Low	Low	Medium	High	Low

All hardware components were selected to satisfy the design priorities identified by the co-design focus groups (Section 3.4.2.4) and to meet the technical criteria established in the preceding literature review (Chapter 2). Initial prototypes of the dosage tracker resulted in a system composed of an Arduino Nano 33 IoT, PN532 NFC reader, mini breadboard, a power supply and connecting Dupont wiring within a compact PLA enclosure.

4.2.1.1. Arduino Nano 33 IoT

The Arduino Nano 33 IoT is a small microcontroller board (45 × 18 mm, ~5 grams) designed for Internet of Things (IoT) applications. It carries the Microchip SAMD21 Arm Cortex-M0+ 32-bit processor, along with a NINA-W102 radio module for Wi-Fi and Bluetooth connectivity. The board also includes a 6-axis IMU (LSM6DS3 accelerometer/gyroscope) and a Microchip ATECC608A for secure communication (Figure 15).

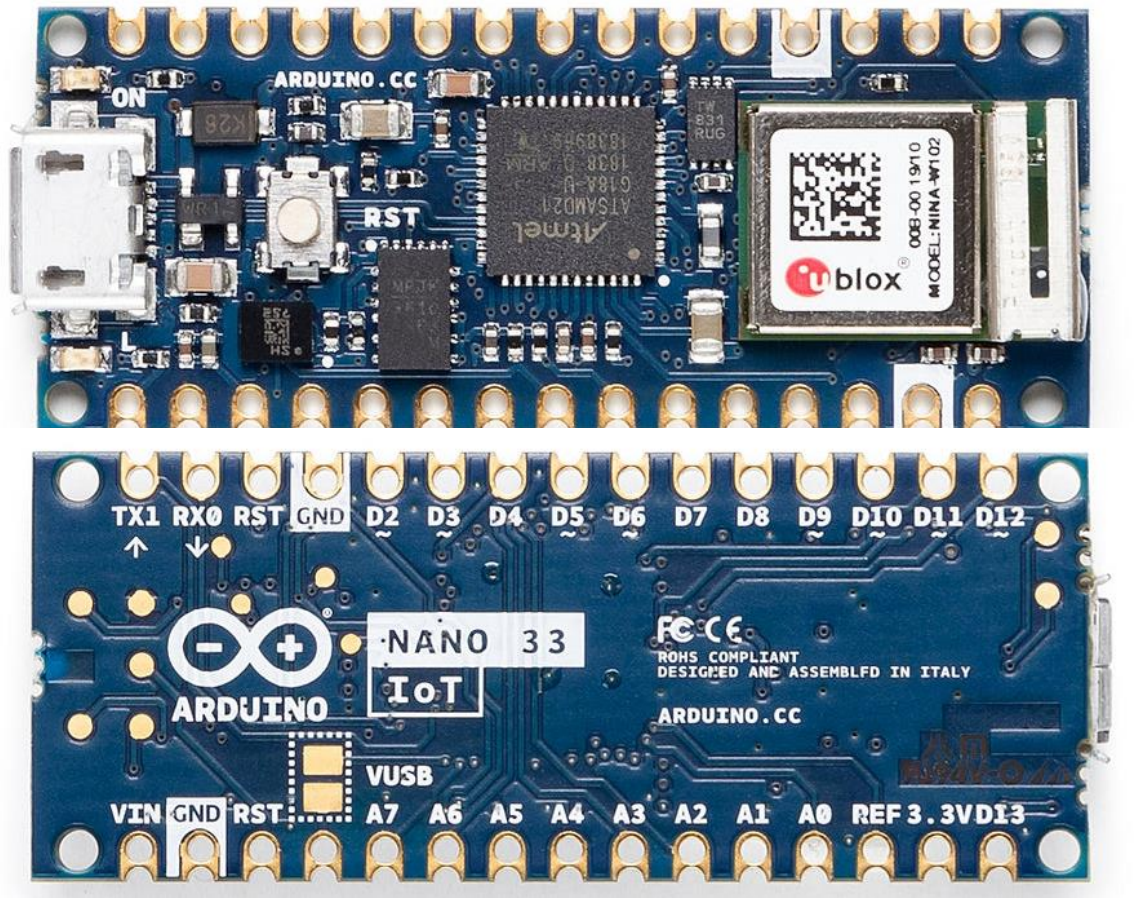


Figure 15 Arduino Nano 33 IoT (Arduino, 2025)

Its 32-bit Cortex-M0+ microcontroller runs at 48 MHz, providing adequate processing speed for reading sensors, running simple algorithms, and handling real-time tasks. It has 256 KB of flash memory and 32 KB of RAM, enough to store the proposed DAIM logic and buffer sensor data.

The board's IMU allows precise movement tracking, measuring acceleration and rotation on three axes each. This IMU can be configured across multiple sensitivity ranges (up to ±16 g acceleration and 2000 °/s rotation) and can sample at 100 Hz or more. In practice, researchers have successfully used the Arduino NANO 33 IoT board's built-in 6-axis IMU, specifically the LSM6DS3 from STMicroelectronics, as part of the G-STRIDE device, to monitor gait and limb movement (García-Villamil et al., 2021). G-STRIDE, utilising this IMU, demonstrated high estimation accuracy for the walking speed of the elderly and good concurrent validity compared to conventional measures (ICC=0.69; $p < 0.000$) (García-Villamil et al., 2021).

Another important feature is the board's low-power architecture, which is critical for battery-powered wearables. The combination of the efficient ARM MCU and the low-power NINA W102 radio helps maximize battery life (Arduino, 2025). The DAIM is designed to be used for extended exercise periods, so the ability to run on a small battery for hours is essential. The Nano 33 IoT operates at 3.3 V and is designed to consume minimal power when running typical sensor and communication tasks.

Its small size and weight, as described earlier, also contribute to wearer comfort as it can be attached to the body. The Nano 33 IoT also provides 14 digital I/O pins and multiple analogue inputs, so additional sensors can be connected if needed.

One of the strongest advantages of the Nano 33 IoT is its built-in wireless capabilities. It includes a NINA-W102 module, which provides both Wi-Fi and Bluetooth Low Energy (BLE) connectivity on the 2.4 GHz band. The design spec of the intensity tracker requires the use of

BLE to live-stream the movement data and so it is important to select a microprocessor that can support this. The Arduino also is very developer friendly, connecting the Nano 33 IoT to a network or phone does not require deep networking expertise as the board is supported by high-level libraries and examples.

An additional advantage to using Arduinos is that it is relatively cost-effective, currently priced about £25 per unit. This allows the project to create multiple wearables without a huge investment. If a device gets damaged during a study, then replacing the core microprocessor is not detrimental. Cost is an important feature of adoption, folk need to afford it

The Nano 33 IoT can be programmed via the Arduino IDE using straightforward C/C++-based sketches. There is no need to write low-level device drivers for the onboard sensors or other components as Arduino provides high-level libraries (e.g. for the IMU, WiFiNINA, ArduinoBLE) that remove the complexity. Finally, the Nano 33 IoT can be powered via USB or battery and can be connected to a computer with a single cable for programming making it very accessible for rapid prototyping and iteration where changes can be made to the DAIMs firmware daily.

4.2.1.2. Other Components

To recognise each user-tag and timestamp activity automatically, the prototype employs a PN532 breakout board operating at 13.56 MHz (Figure 16). The PN532 supports the ISO 14443 standards for how contactless cards and terminals should work to ensure industry-wide compatibility, and NFC Forum type-2 tag standards, which means it can read low-cost MIFARE Classic S50 cards, ABS key-fobs and printable sticker tags all of which are very common to procure.

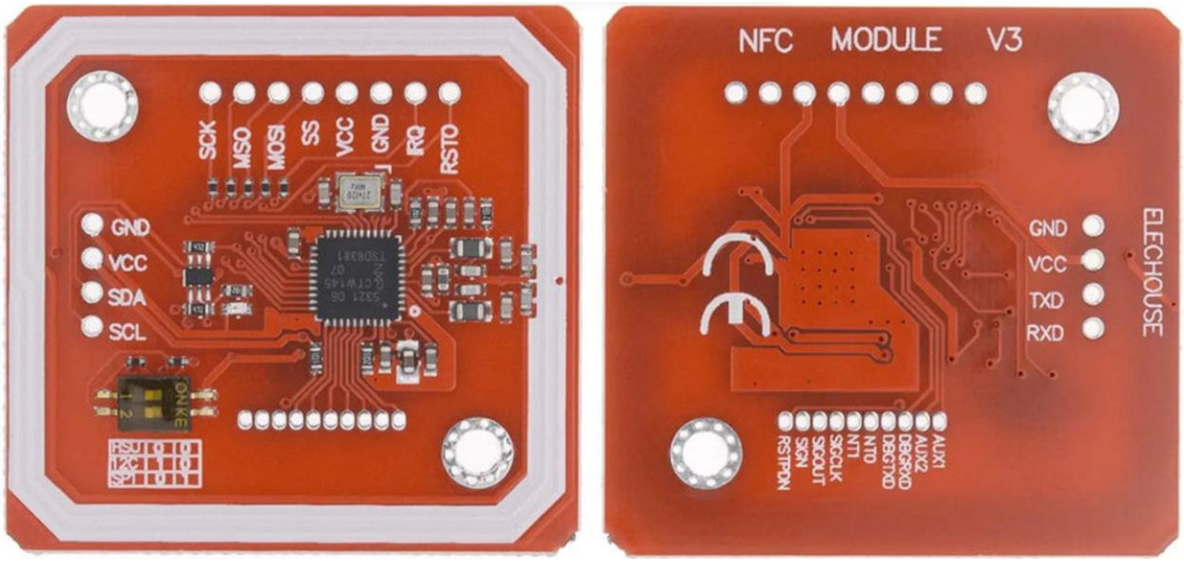


Figure 16 Front and back of NFC module (without header)

The board utilises Inter-Integrated Circuit (I²C), Serial Peripheral Interface (SPI) and Universal Asynchronous Receiver/Transmitter (UART) interfaces. I²C was selected because it minimises pin usage on the Arduino Nano 33 IoT and is fully supported by the Adafruit PN532 library, allowing reliable tag detection with a single high-level command (nfc.readPassiveTargetID()). The NFCs antenna provides a 40 mm footprint and gives a read range of ~30 mm through the PLA lid (Section 4.2.3).

The PN532 NFC module is linked to the Arduino Nano 33 IoT with short, colour-coded Dupont jump-wires that plug into the module's header and the mini breadboard. Power and logic lines follow the I²C convention used elsewhere in the system: VCC (3V) and GND supply the reader, while SDA and SCL connect to the Nano's dedicated I²C pins (A4 and A5). A fifth Dupont lead routes the PN532's IRQ/REQ line to a spare digital-input pin so that the firmware can wake instantly when a tag enters the antenna field. Using loose Dupont leads instead of soldered ribbon keeps the prototype flexible for iterative changes.

In the forthcoming hardware revisions prompted by both AHP (three physios and an OT) and stroke participant feedback, audio and visual feedback channels were integrated into the circuit (Section 4.3 & 4.4). A 5 Ω mini speaker was implemented to a LM386 Chip Audio Amplifier

Board to deliver clear audible cues, one tone for a successful scan-in/out and a distinctive triple-beep for errors. Therefore, users with visual or cognitive impairments receive immediate feedback without needing to view the tracker's LED feedback.

Visual feedback was implemented using two 5 mm LEDs: a green LED that flashes once for "scan-in" and twice for "scan-out", and a red LED that signals any read error. Each diode was driven from its own GPIO pin through a 330 Ω current-limiting resistor, ensuring brightness is consistent yet well within the Nano's safe sourcing limits (Figure 17, Figure 18).

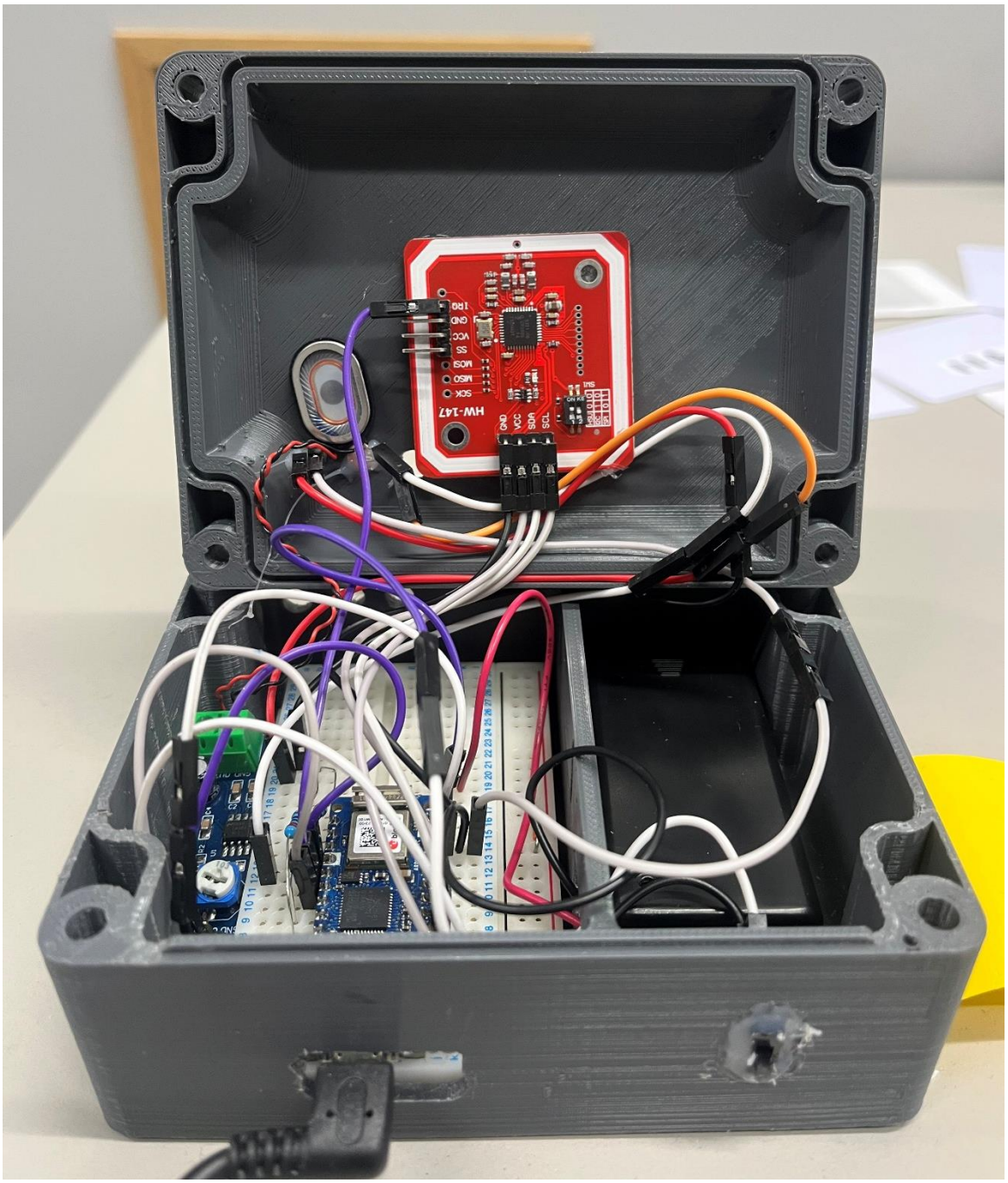


Figure 17 Picture of final iterative dosage tracker with inner circuitry.

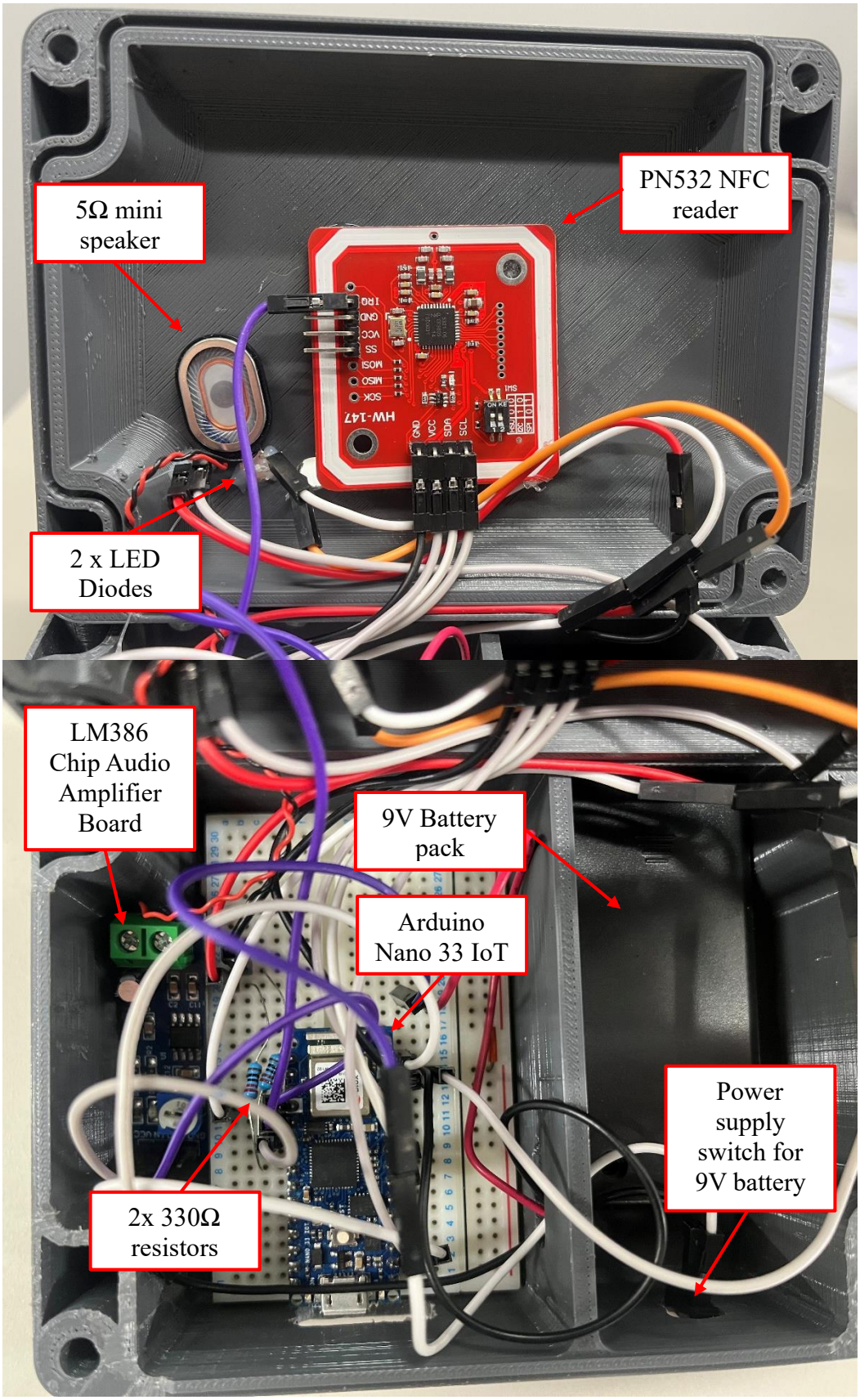


Figure 18 (Top) inner lid of dosage tracker with components highlighted, (bottom) inner base of dosage tracker with components highlighted

4.2.1.3. Dosage System Overview

Table 9 summarises the hardware and software layers that make up the NFC-based dosage tracking system. All tag types (disposable sticker, S50 card, ABS key-fob) are encoded in the NFC Data Exchange Format (NDEF), allowing the PN532 reader, powered by the Arduino Nano 33 IoT and programmed in C++, to recognise any of them with identical logic.

Each successful scan produces a small JSON payload (UID, device ID, timestamp) that the micro-controller sends, via the centre's local secure Wi-Fi, to a lightweight Flask server. The Flask application, written in Python, receives these HTTP requests, gives them a timestamp, then stores the records in a local log later analysis on a Raspberry Pi (Figure 19). This architecture keeps the on-body firmware efficient, off-loads storage to the server, and uses only open, low-cost components. This prototype prioritises affordability, ease of maintenance, and straightforward data handling.

Table 9: Summary of the system environment within the rehabilitation dosage tracking system, detailing the potential data formats handled and their respective functions.

System part	Data formats	Description
Flask Server	Python, HTTP	Manages and responds to HTTP requests.
NFC sticker tags	NFC Data Exchange Format (NDEF)	Provides secure and contactless data transmission or identification.
S50 RFID Cards	NDEF	Provides secure and contactless data transmission or identification.
ABS Keyfob	NDEF	Provides secure and contactless data transmission or identification.
NFC reader: Arduino nano 33 IoT and PN532 module	C++, HTTP, JSON	Reads NFC tags and communicates the data to other systems.

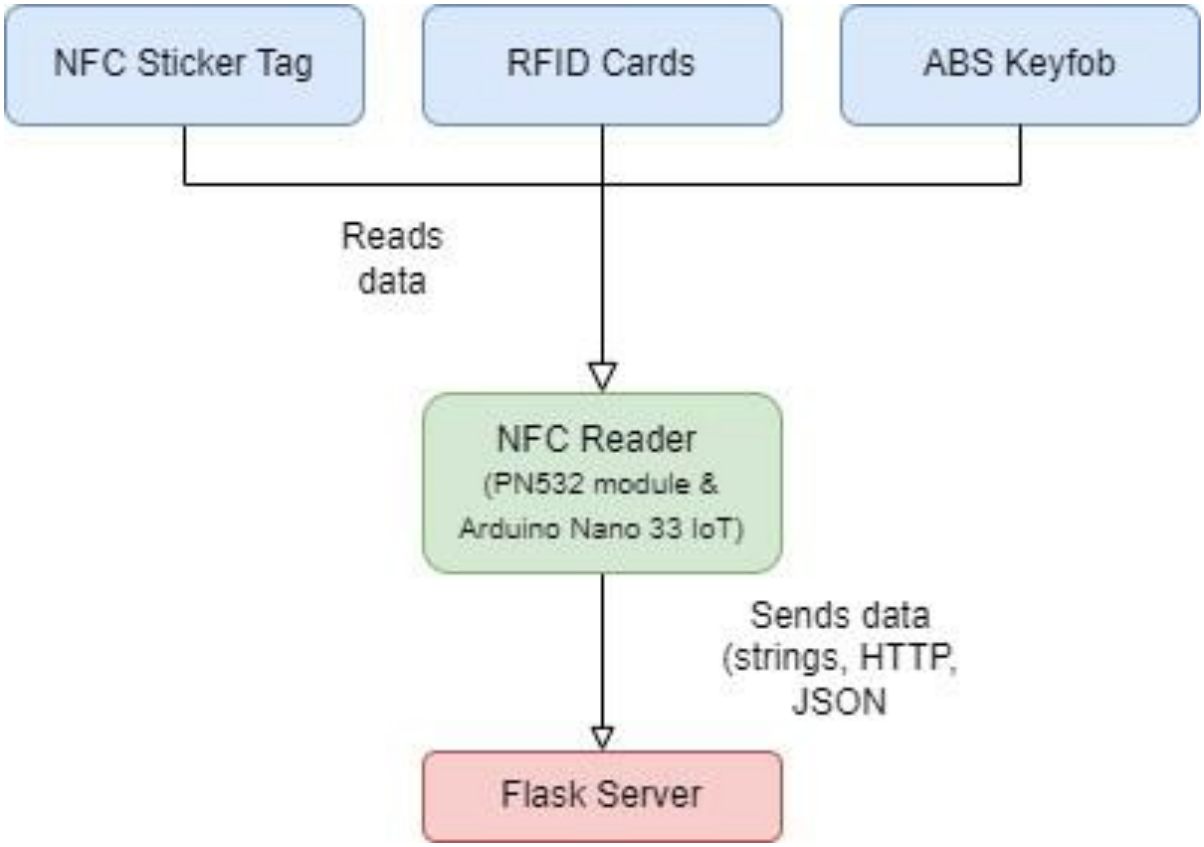


Figure 19: Flowchart depicting the potential data flow of the NFC-based identification system.

4.2.2. Software Development

4.2.2.1. Arduino

Firmware was written in C++ (Arduino API, IDE 2.3.2) and organised as a single compilation script (Appendix 3).

When the device is first turned on, the startup process (setup()) goes through three main steps. First, the internal clock is set with the current date and time. This clock continues to track time accurately while the device is running. Second, the NFC card reader is activated so it can detect when users tap their cards. Finally, the device connects to the local Wi-Fi network. Only after all these steps are complete does the system check if there's already any session history stored

from previous use. If it’s the first time the device is being used, it prepares a blank memory for tracking user activity.

The main functionality happens continuously in the loop() part of the code. Whenever someone taps their NFC card, the device checks to make sure it isn’t a repeat scan from the last two seconds (to avoid duplicates). If the tap is valid, the device captures the unique ID from the card. It then looks through its saved memory to see if this card has been used before.

In memory, the device can store up to 50 users. For each user, it saves their card ID, up to 10 login times, 10 logout times, and whether they are currently logged in. If the card has been used before, the device finds that user’s record. If not, it creates a new one.

When a returning user taps their card, the device decides if this is a login or a logout based on whether they are already marked as "logged in." If it’s a logout, the device calculates how long the session lasted by comparing the current time with their most recent login. It then prints out a short summary showing how long the session was.

After logging out, the device sends the session details (such as duration and the name of the device, like “Shapemaster”) to a local server. For new users, only the first login is saved, and nothing is sent to the server until they log out the next time. No matter if it’s a login or logout, the device always saves the latest user data immediately, to ensure it doesn’t lose anything if the power is cut or it restarts.

For maintenance, the device also responds to two special commands sent over a USB connection. One command, FETCH_DATA, shows all the saved user records on a connected computer. The other command, RESET_STORAGE, erases all saved data and starts the system fresh. Figure 20 shows the coding hierarchy of the dosage systems initial prototype, highlighting the two key features of code (setup() and loop()) and their accompanying functions.

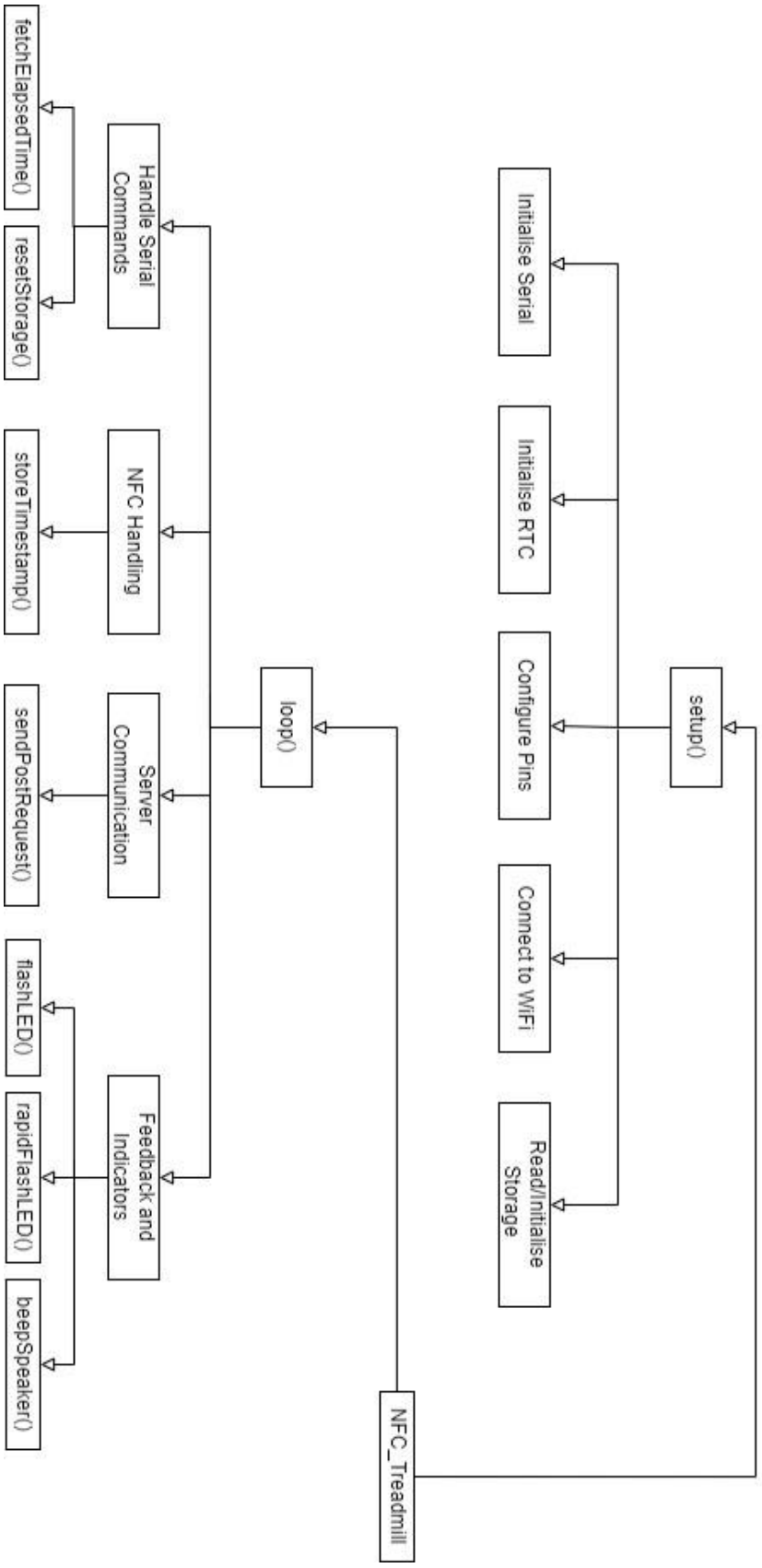


Figure 20: Flowchart illustrating the operational logic of the dosage tracking (Titled: NFC_Treadmill) system.

4.2.2.2. Flask Server

Once the Arduino finishes recording the time for a rehabilitation session, it passes the information to a lightweight server application written in Python using a framework called Flask. The full server script is available in Appendix 4. The Arduino sends the session data over Wi-Fi using a standard internet message format called an HTTP POST request. This message includes the user's card ID (UID), how long the session lasted, and the name of the rehabilitation machine.

As soon as this message reaches the server, a specific part of the Flask program (marked @app.route('/postdata', methods=['POST'])) is automatically triggered. This part of the code quickly pulls out the details sent by the Arduino and combines them with the server's own timestamp to create a complete session record.

This record is then saved into a log file stored on a USB drive that's connected to a Raspberry Pi processor. The Raspberry Pi stays running alongside the Wi-Fi server to make sure that session data is safely backed up. It also helps share that data with the mobile app used for monitoring or reviewing progress. Because the data is stored on a separate USB drive, it remains safe and accessible even if the Raspberry Pi itself is restarted or loses power.

4.2.3. Enclosure and Physical Design

The dosage-tracker enclosure was designed in SolidWorks and fabricated on a desktop fused-filament 3-D printer using grey (polylactic acid) PLA filament (Solidworks drawings in Appendix 2).

PLA is frequently selected for rehabilitation-engineering enclosures because it satisfies the practical demands of busy gyms and wards. FDM printing studies have shown that PLA produces stiff, dimensionally stable shells that tolerate repeated donning and doffing during

gait-training sessions while keeping raw-material costs to a minimum (Elmowafy et al., 2019; Joseph et al., 2023; Oleksy et al., 2023).

Mechanical testing further indicates that medical-grade PLA exhibits negligible creep at room temperature across the load ranges typical of wearable supports, so printed housings remain accurate even after prolonged use or storage on equipment trolleys (Gramala et al., 2021). Equally, PLA surfaces can be disinfected effectively with standard alcohol wipes and reused without warping or delamination, meeting infection-control requirements in clinical environment (Luchini et al., 2021).

The finished enclosure measures 120 mm × 90 mm × 56 mm which was deemed large enough to shield the electronics yet compact enough to rest unobtrusively beside a rehabilitation workstation. Internally the shell is divided into two bays: a 79 × 61 × 40 mm compartment for the Arduino stack and PN532 reader, and a 79 × 39 × 40 mm bay for the power source. A 2.45mm internal channel links the bays, carrying the battery leads to the mini breadboard, while a 2.14mm external space provides USB access for firmware uploads and debugging.

The cover and base interlock with a 1.5 mm tongue-and-groove lip that keeps the halves aligned and affords splash protection during routine disinfecting. Four countersunk M3 screws pass through 4.64mm bosses, allowing the unit to be securely fastened to a wall or equipment frame if required. To preserve NFC sensitivity, the lid thickness directly above the PN532 antenna is limited to 1.4mm, and the antenna itself is bonded to the inside of the cover so that the tags are as close to the reader as possible.

Inside the electronics bay (Figure 18), the Arduino stack is seated on a self-adhesive mini breadboard fixed to the base. The adjacent battery bay was originally dimensioned for a 9V cell, however over the course of the project's iterations the bay now houses a 5V, 1A rechargeable power bank to extend run-time and reduce operating costs.

4.3. Pilot Study: Feasibility and Accuracy of the Dosage Tracker

4.3.1. Introduction

Following the development of the initial dosage tracking prototype, this study marked the project's transition into the 'Feasibility' phase of the MRC framework. The primary aim was to assess the technical accuracy, usability, and practical feasibility of a digital rehabilitation dosage tracker built using an Arduino-based NFC logging system. This component was designed to monitor the frequency and duration of rehabilitative activities in a research gym setting using healthy volunteers, with the long-term goal of translating this functionality to real-world settings.

A small-scale observational study design was used to evaluate both the system's functionality and user experience under controlled, yet realistic, conditions. Insights gained from this study would support iterative refinements to the prototype ahead of its implementation within stroke rehabilitation users.

4.3.2. Methods

4.3.2.1. Participants

Participants were recruited from the staff and volunteer network supporting the TERG stroke rehabilitation gym at the University of Strathclyde. Inclusion criteria required that participants were either (1) regular staff or volunteers involved with the TERG rehabilitation cohorts, and (2) available to attend a one-hour session during standard working hours (Monday to Friday, 9–5). Exclusion criteria included (1) individuals who were unwell during the study period or taking medication that could affect their ability to walk safely on a treadmill, and (2) those with physical impairments that would prevent them from participating in the study task.

This participant group was deliberately chosen because they also represented key stakeholders in the DAIM system's future as AHPs, engineers, and academics who may ultimately support or deliver the system in clinical or research settings, their involvement offered valuable insight. Additionally, recruiting from this stakeholder pool allowed for the collection of spontaneous, experience-informed feedback that could directly inform subsequent design iterations.

4.3.2.2. Setup

Participants interested in the study received an information sheet outlining the study objectives and procedures and were required to sign a consent form prior to participation. The study was conducted at the University of Strathclyde's TERG facility, where a dedicated space was prepared to simulate a typical rehabilitation environment. This included a weight-supported treadmill, and the digital dosage tracker mounted on a 63-inch tablet gooseneck floor stand (Figure 21).

Participants were first given a demonstration of the dosage tracker and shown how to operate the system under simulated rehabilitative conditions. A separate logging and survey station was set up nearby, containing three different NFC logging options: (1) five white NFC cards, (2) five key fobs, and (3) two exercise wristbands with visible white NFC stickers (Figure 22). The availability of only two wristbands was due to time constraints and limited supply. The station also provided the SUS questionnaires, which participants were instructed to complete and return after finishing the study tasks.

To validate the accuracy of the digital tracker, a Samsung smartphone was positioned beside a MOTEK C-mill HERO treadmill (Motek Medical, Netherlands), to video record participants' interactions with the system (Figure 21). Video footage was later used to cross-check the actual exercise start and end times against the timestamps recorded by the dosage tracker. Although all participants were familiar with the treadmill and its role in stroke rehabilitation, a brief

refresher was provided to ensure proper use of the machine and weight-support hoist. For safety, participants completed the treadmill task individually under supervision.

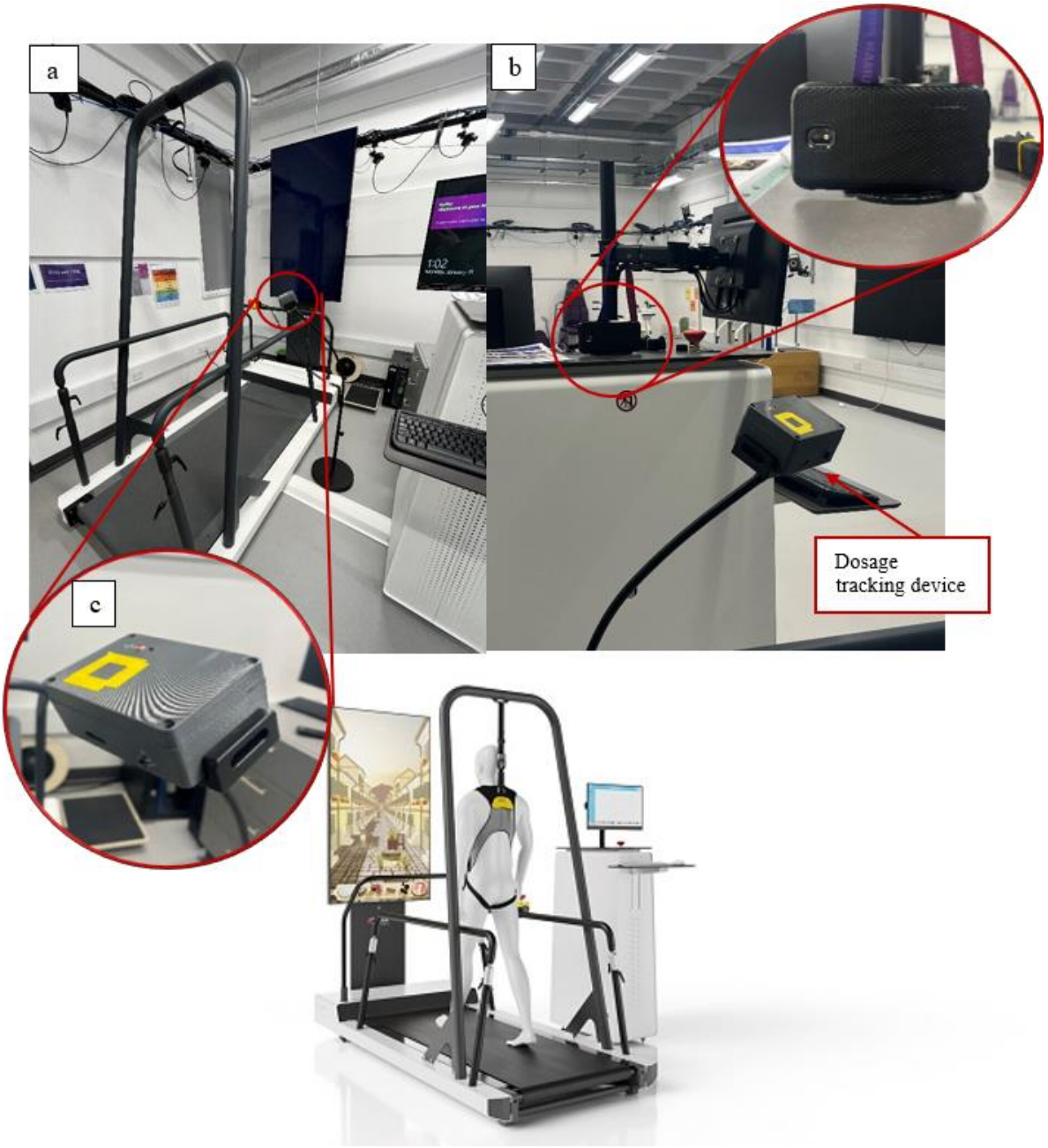


Figure 21 Experimental setup (a) depicts how the dosage tracking system was situated next to the MOTEK C-mill HERO (Motek Medical, Netherlands), (b) shows how the mobile phone was used to film participants as they were walking on the treadmill with (c) showing a close-up view of the system.

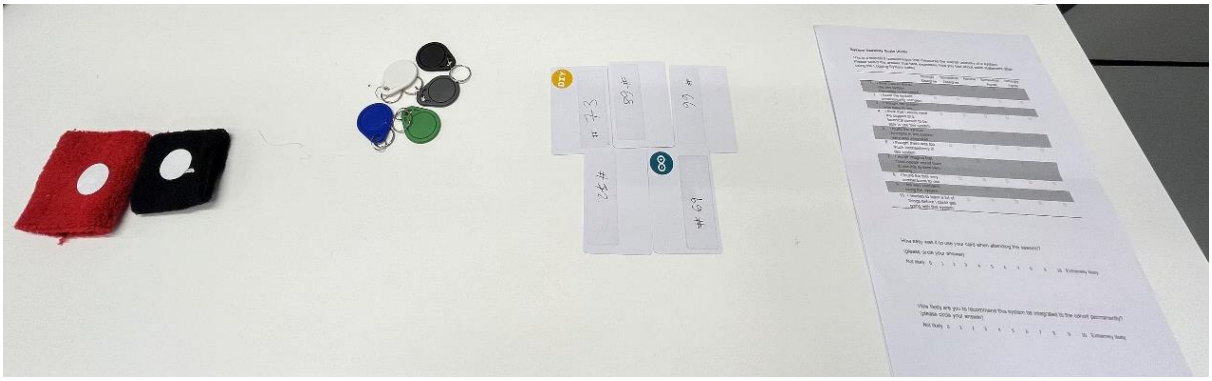


Figure 22 Table setup including all NFC logging items and accompanying SUS survey.

The key task of each participant was to use the dosage tracker before and after a one-minute walking session at a speed of 1 kph. Each participant completed this cycle three times, once with each of the three NFC logging methods. After completing all three sessions, participants filled out a SUS questionnaire. They were not required to follow a specific order when selecting NFC logging items, and reuse of NFC logging items by multiple participants was permitted, as unique identifier (UID) tracking was not within the scope of this initial study and would be addressed in future investigations.

4.3.2.3. Data Collection: NFC

The Flask server was programmed to log key data points each time an NFC item was scanned by the dosage tracker. Specifically, the system recorded: (1) the unique identifier (UID) of the NFC logging item, (2) the name of the corresponding Arduino device, (3) the duration between the first scan (marking the start of the exercise) and the second scan (marking the end), and (4) a timestamp indicating the exact date and time of session completion. For the purposes of this pilot study, all data were extracted for analysis except the specific UIDs, which were not required.

4.3.2.4. Data Collection: The System Usability Scale (SUS)

The SUS is a 10-item questionnaire that provides an overall measure of a system's usability (Appendix 9). Responses are given on a 5-point Likert scale ranging from 1 (totally disagree) to 5 (totally agree). The SUS includes five positive and five negative statements, and the scores are converted into a final value ranging from 0 (negative) to 100 (positive). For each item, the response is transformed so that all items contribute in the same direction. For positively worded (odd-numbered) items, the transformed score is computed as:

$$S_i = r_i - 1$$

and for negatively worded (even-numbered) items, it is computed as:

$$S_i = 5 - r_i$$

where r_i is the response for item i. The contributions from all 10 items are then summed:

$$Total\ Score = \sum_{i=1}^{10} S_i$$

Finally, the total is multiplied by 2.5 to obtain the final SUS score:

$$SUS\ Score = Total\ Score \times 2.5$$

Whilst this does provide a numerical measurement of the systems usability, determining what is 'acceptable' does vary across published literature depending on the systems application and target users (e.g. clinical applications vs standard commercial). Some literature define products as 'passable' when they have achieved a SUS score of 70 or above, with better products scoring 75-85 and superior products scoring better than 90 (Figure 23) (Bangor et al., 2008). Other literature interpret the SUS benchmark as a curved grading scale (Figure 24) (Lewis, 2018).

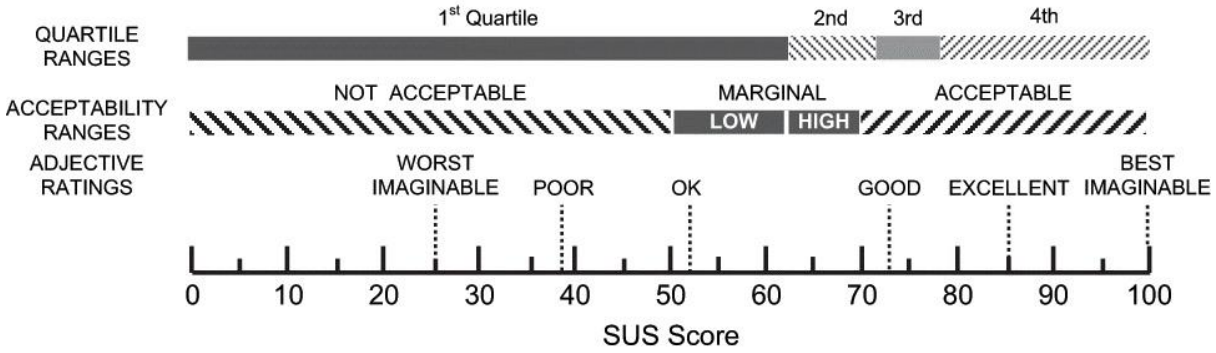


Figure 23 A comparison of mean System Usability Scale (SUS) scores by quartile, adjective ratings, and the acceptability of the overall SUS score (Bangor et al., 2008).

Grade	SUS	Percentile range
A+	84.1 - 100	96 - 100
A	80.8 - 84.0	90 - 95
A-	78.9 - 80.7	85 - 89
B+	77.2 - 78.8	80 - 84
B	74.1 - 77.1	70 - 79
B-	72.6 - 74.0	65 - 69
C+	71.1 - 72.5	60 - 64
C	65.0 - 71.0	41 - 59
C-	62.7 - 64.9	35 - 40
D	51.7 - 62.6	15 - 34
F	0 - 51.6	0 - 14

Figure 24 Curved grading scale for SUS (Lewis, 2018).

Literature surrounding the use of SUS surveys for digital health applications, however, suggest that a simple benchmark of 68/100 is adequate, as this is the line where 50% of apps fall below or above it (Hyzy et al., 2022; Sauro & Lewis, 2016).

Despite the lack of consensus on interpretation, the SUS is considered a reliable assessment (Cronbach's alpha = .91) and is widely used in user-centred design (Bangor et al., 2008). This means that results can be compared to existing literature (Bangor et al., 2008; Knippenberg et al., 2021). Additionally, the SUS is short and so minimises burden on the users whilst still yielding robust data. The SUS is therefore an appropriate method for assessing the usability of the DAIM.

4.3.2.5. Data Management and Analysis

The video recording was extracted after the study concluded and stored electronically in a private folder within the investigations primary, password-protected OneDrive folder for up to five years (Microsoft Office, 2024). Additionally, the video recordings used to validate the NFC's accuracy did not capture participants' faces, maintaining participant anonymity. The data gathered from the Flask server was initially presented as a .CSV file, as per the design of the server, and then uploaded to Microsoft Excel 2016 (Microsoft Office, 2024) to be filtered and processed then later stored in the same password-protected OneDrive folder. The total time error of each activity was calculated and plotted with a regression analysis conducted. An ANOVA: Single Factor was used to find any significance between the use of each method of NFC logging. The SUS survey results were also manually inputted into Microsoft Excel 2016, to calculate the SUS score of each participant, from this the mean and standard deviation of the scores were calculated. All physically completed SUS surveys were then stored in a locked filing cabinet.

4.3.2.6. Ethics

This pilot study was conducted under ethical approval from the Strathclyde University Ethics Committee (protocol number UEC20/08 Kerr, Appendix 13).

4.3.3. Results

Five healthy participants were recruited for the study. The five participants comprised of one research assistant in sports therapy, a research assistant who was a practising occupational therapist, a senior lecturer who was a qualified physiotherapist, a postgraduate engineering student, and a research physiotherapist all of whom specialise in rehabilitative engineering and are employed or volunteer at the TERG.

4.3.3.1. System Performance Summary

Table 10 outlines the system's performance across six key operational scenarios during 15 total activity logging attempts. The system demonstrated a high success rate, with one logging error occurring during a key fob authentication attempt, resulting in a 93.3% success rate across five of the six scenarios. Notably, the Flask server maintained a 100% success rate and stable connection throughout the session.

Table 10: Overview of system performance across the six, core scenario occurring within the system when undergoing the 15 activity attempts.

Scenario	Core Function	Attempts	Success	Comment
1	Data received: UID	15	93.30%	UIDs all sent to server except errored attempt
2	Data received: session duration	15	93.30%	Session durations all sent to server except errored attempt
3	Data received: activity used	15	93.30%	Activity device names all sent to server except errored attempt
4	NFC read correctly	15	93.30%	One NFC key fob did not read correctly, and so data was not sent to server and Arduino required reset
5	Hardware operation	15	93.30%	Arduino required one hard reset after one error was detected
6	Server operation	15	100%	Server remained connected to Arduino

				entire session, no need to reset. CSV file was correctly produced

4.3.3.2. Absolute Error Analysis

To assess timing accuracy, the time logged by the NFC system was compared to the actual duration of treadmill usage recorded via video analysis. Figure 25 presents a line graph showing the total error per session across 14 successful attempts. A regression analysis of error over time (represented by attempt number) returned an R^2 value of 0.20 and a p-value of 0.11. These findings indicate no statistically significant trend in reduced error over time, although a slight downward trend was visually observed.

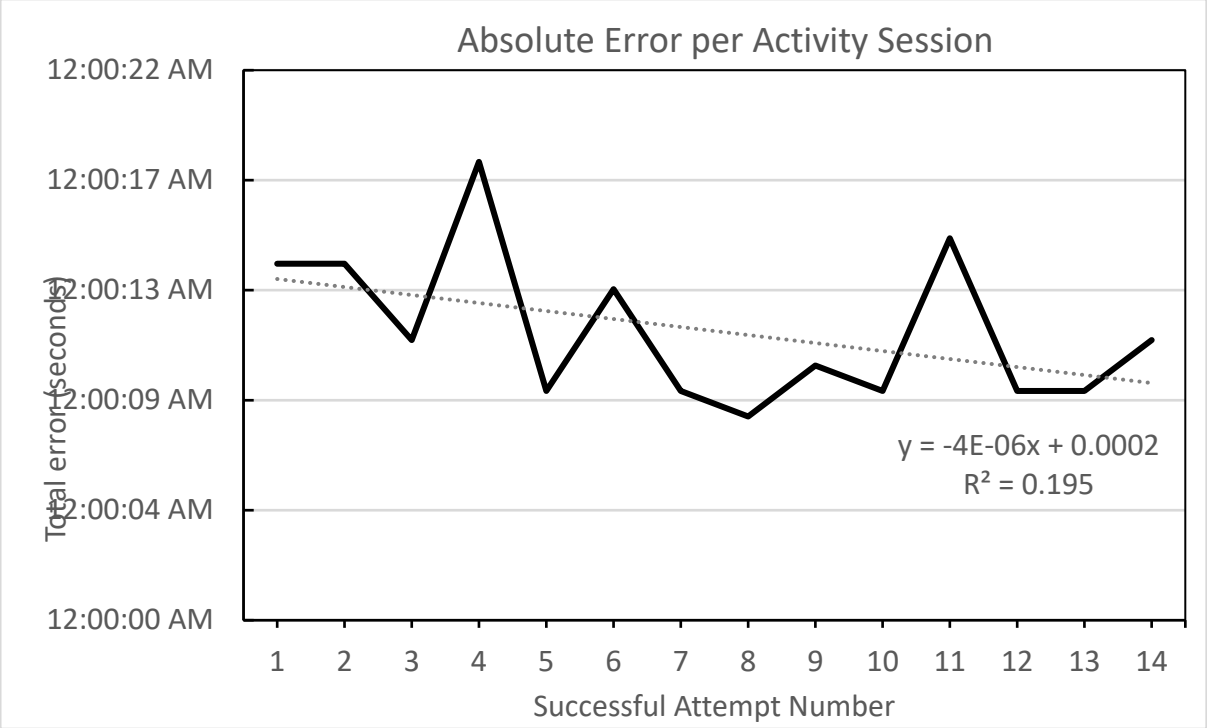


Figure 25 Line graph depicting the total error per activity session over 14 successful attempts. A dotted trend line shows a slight negative correlation.

4.3.3.3. NFC Performance

Figure 9 compares the minimum, maximum, and average absolute error for each type of NFC device (Card, Key Fob, Wristband). Table 11 and Figure 26 presents the summarised error metrics. The card method produced the lowest average error (10 seconds), followed by the wristband (11 seconds), and key fob (14 seconds).

Table 11 Average error of each NFC logging device: wristband, card, and key fob

Device	Minimum Error (seconds)	Maximum Error (seconds)	Average Error (seconds)
Card	8	14	10
Key fob	9	18	14
Wristband	9	15	11
Absolute	8	18	12

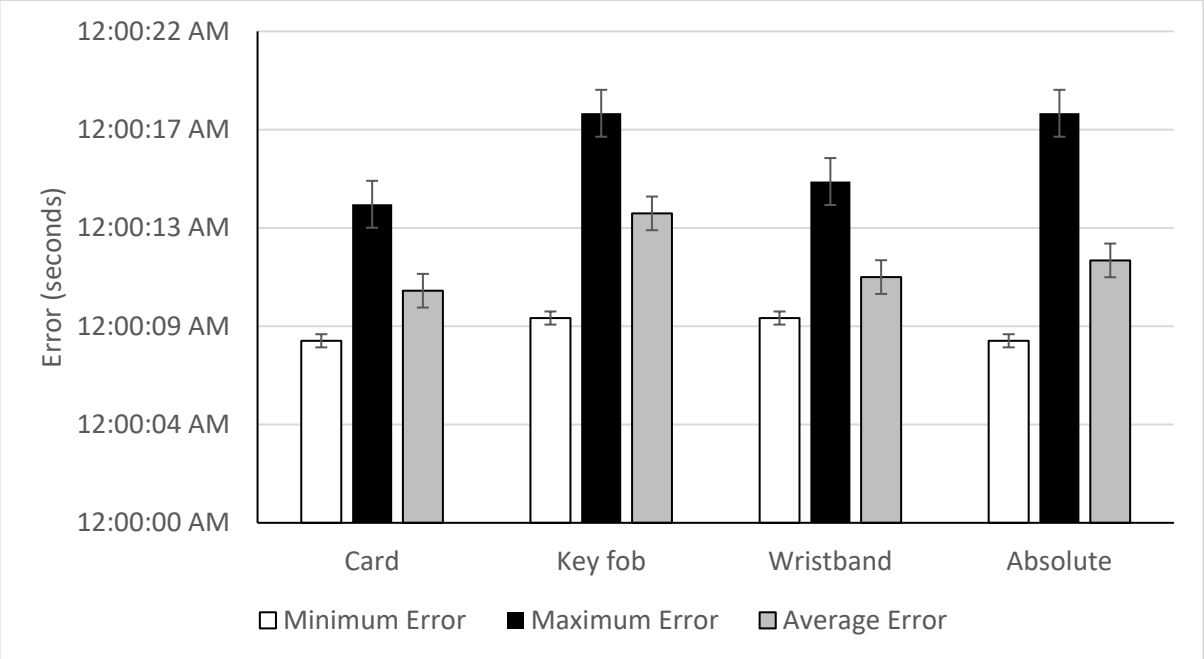


Figure 26: Clustered bar chart displaying error times in seconds for different authentication devices: Card, Key Fob, Wristband, and Absolute. Each device category has three bars representing minimum, maximum, and average error, respectively, with error bars.

An ANOVA test was conducted to examine whether differences in average absolute error across logging devices were statistically significant. The results (F=1.15, p=0.36) indicated no

significant difference between the groups, suggesting that participants could use any logging device interchangeably without compromising accuracy.

4.3.3.4. SUS

High usability was demonstrated with a mean SUS score of 96/100 (SD 4.90); the total SUS score was calculated based on participants' responses to the 10-item questionnaire, with each item rated on a 5-point Likert scale. The scores were normalised and converted to a range of 0-100. Recommendation scores ranged from 8 to 10 out of 10, with participants noting ease of use, confidence in operation, and perceived consistency of the system. Importantly, all participants disagreed with negative statements about complexity and inconsistency. It was found that 60% of users favouring the card, likely due to its familiarity and perceived ease of use. The wristband and key fob each received 20% of user preference.

4.3.3.5. Server Output

All successfully completed attempts resulted in the expected server-side printout, which included:

```
2023-10-04 12:11:14 UID: 048443454f6180 | Name: Treadmill | Session
Duration: 0 hours, 12 minutes, 48 seconds |
```

4.3.4. Discussion

This pilot study assessed the performance and usability of the digital dosage tracking system using healthy participants who were staff or volunteers at the TERG. The aim was to compare digitally logged rehabilitation dosage with actual exercise duration, while also evaluating system usability and identifying potential points of refinement before larger-scale implementation.

The system successfully logged 15 rehabilitation activities with a 93.3% success rate. A single error occurred during the third trial when a participant used a key fob, likely due to the fob not

being held close enough to the NFC reader. This issue was compounded by hardware limitations: the chosen NFC module lacked a reset pin, meaning a full Arduino reset was required to recover functionality. While this did not affect the server's operation which maintained a 100% uptime and quickly reconnected, this scenario highlights the need for future iterations to include more robust hardware with integrated reset functionality, such as the NFC module. Nonetheless, all correctly logged activities produced the expected data outputs, validating the system's basic functionality. Throughout the investigation, except for the isolated error incident, all essential data categories including user UID, session duration, and activity type, were accurately sent to the Flask server and were printed in the correct format coded into the Flask server.

The difference between scan times and actual exercise start/stop times was a key focus, captured using video recordings and calculated as the 'absolute error'. These small delays caused by users positioning themselves on the machine or storing their NFC tag, were expected. Importantly, users became more efficient over time; the maximum error reduced from 18 to 15 seconds after 10 sessions, indicating a brief learning curve. The average absolute error across all trials was 12 seconds, with NFC cards producing the lowest average error (10s), followed by wristbands (11s) and key fobs (14s). This also suggests user familiarity with cards may offer more precise scanning behaviour.

The average absolute error is an important metric in evaluating the efficacy of the dosage tracking system. Results showed the average absolute error was closer to the minimum error than the maximum error, indicating that the system was performing relatively well and did not require significant refinements (Table 11). If the average error were closer to the maximum error, it would suggest a need for refining the logging mechanism before considering a larger-scale implementation of the system. This margin of error is also important when considering future integration with the DAIM mobile app. For example, the app features daily progress

bars that reflect a user's equipment usage time. Based on the study findings, incorporating a 12-second buffer into these bars would help account for these common scan-to-exercise transition delays without compromising accuracy.

Usability was assessed via a SUS, where participants overwhelmingly rated the system positively. Most indicated they would use the system frequently, found it easy to learn, and believed it integrated well with the rehab setting. The lowest recommendation score was 80%, and over half the participants preferred the card-based NFC method, particularly for its familiarity and simplicity. These results suggest the system is intuitive, minimally disruptive, and requires little additional training.

These findings support the system's potential for seamless integration into TERGs current rehabilitation workflow. The strong user confidence and positive perception of system simplicity are encouraging, especially given the intended target population of individuals with stroke, many of whom may have cognitive or physical impairments. When looking to implement this further into a clinical setting, disinfection will play a key role and it was recommended by an occupational therapist during the investigation that the card was the most appropriate for infection control as it could be disinfected with an alcoholic wipe or spray, the key fob could have too many small spaces that may cause a build-up of bacteria and the wristband would need to be made of a specific and completely waterproof material.

At present, dosage tracking at the TERG is done manually, with staff recording estimated equipment usage on paper forms later stored securely. This method is inherently susceptible to human error, especially as staff juggle data recording with assisting participants. The next study will directly compare the digital tracker's performance to this manual system. Based on the current findings and strong SUS scores, the digital system appears viable as a more accurate

and efficient alternative, capable of reducing documentation errors and enhancing data collection quality.

4.4. Tracking Rehabilitation Dosage in a Research Gym (TERG): Usability and Accuracy Study

A version of this study has been published in JMIR Rehabilitation and Assistive Technologies (Boyd et al., 2025).

4.4.1. Introduction

Building on the previous investigation, which introduced and evaluated the DAIM system in a controlled setting, this study focuses on its application in a research rehabilitation environment. Currently, the TERG uses a manual logging system to record the rehabilitation dosage undertaken by stroke participants during their 8-week cohort. This study aims to assess the accuracy of the DAIM system by comparing its automatically recorded dosage data with manually recorded times. In addition, usability will be evaluated through the SUS and IMI, to explore how well the DAIM can be implemented within chronic stroke populations. By addressing both the technical performance and user experience, this study seeks to validate the DAIM system's effectiveness within a resesarch setting and lay the groundwork for future implementation in clinical environments supporting acute and sub-acute stroke populations.

4.4.2. Prototype Iteration Development

Building on the findings from the previous pilot study, several key improvements were made to the dosage tracker to enhance usability, user feedback, and power management. A common issue identified was the lack of clear feedback during scan events. To resolve this, an auditory feedback system was added using a Breadboard-Friendly PCB Mount Mini 8-ohm speaker. The Arduino code was also adapted to play a rising tone for a successful 'scan in' and a

descending tone for a successful ‘scan out’. Additionally, to improve error detection, the system was programmed to flash a red LED and play an error tone if an NFC scan failed (Section 4.2.1.3 & 4.2.2.1, Figure 18).

To support easier power management, a SPDT slide switch and a 9V lithium-ion battery was integrated into the circuit, allowing users to turn the device on or off as needed, conserving energy and improving convenience for staff during setup and shutdown.

The design now also adopted the contactless ID card interaction method recommended during the co-design process. Users could tap an NFC-enabled card at any workstation to self-log activity in real time. The tracker was programmed in C++ to identify each user's unique ID via their NFC card, log the associated rehabilitation workstation, and calculate the time spent at that location. Figure 27 illustrates the user journey of the system.

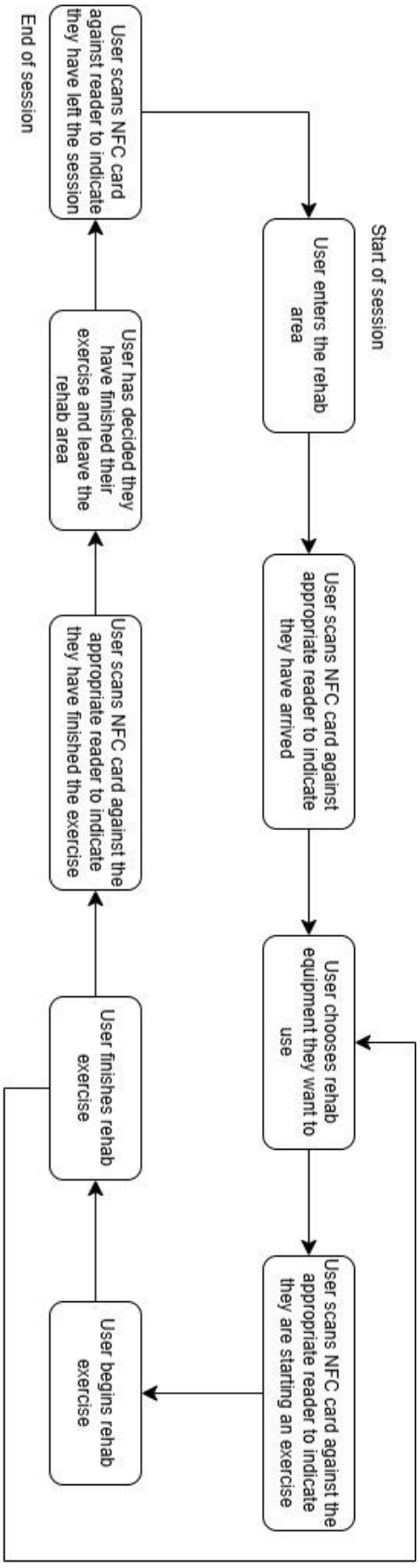


Figure 27 The user journey of the digital dose tracker. NFC: Near-Field Communication; rehab: rehabilitation.

4.4.3. Methods

4.4.3.1. Participants

The study involved nine participants recruited from an ongoing trial (clinicaltrials.gov: NCT06787768) at The Sir Jules Thorn Centre for Co-Creation of Rehabilitation Technology, University of Strathclyde (Kerr et al., 2024; Kerr et al., 2023). That trial was investigating the feasibility of a TERG for people living with stroke, delivered entirely through technology (e.g., virtual reality, treadmills, weight suspension, and power assistance equipment) over an eight-week programme. Individuals in the trial were required to have experienced a stroke at least 12 months prior, be in stable health, and be able to attend at least two two-hour sessions per week, follow instructions in English, and offer verbal or written feedback. Within the TERG, a physiotherapist designed, supervised, and reviewed each participant's programme using principles of intensity, feedback, cognitive engagement, and aerobic activity, aligning it with the participant's goals and baseline outcome measures. Since all nine participants met these criteria, they were also eligible to join the study, providing a controlled environment to evaluate the digital dosage tracking system.

4.4.3.2. Testing

Participants attended routine rehabilitation sessions at the TERG research facility, during which they used the DAIM dosage trackers to log their rehabilitation activities in real time. Following the eight-week usability trial, participants completed the SUS and Intrinsic Motivation Inventory (IMI) surveys to evaluate their experience with the system.

TERG operates six sessions per week, each lasting two hours, with up to eight participants attending at any given time. For this study, five DAIM trackers were deployed in the 'upper limb' section of the facility (see Table 12 for full list). This area was selected due to its smaller size and quieter environment, which allowed participants and staff to focus more easily on

learning and integrating the new tracking system. This was under the recommendation of an Occupational Therapist seconded to the research team from NHS Lanarkshire who suggested that this setup was optimal for user uptake and adaption with minimal distractions; additionally, it would allow for any initial 'teething problems' with the system to be identified and rectified efficiently.

Table 12 Equipment available for study

Equipment	Purpose	Model and manufacturer
GripAble hand trainer	Upper limb training and cognitive training	GripAble, UK
Large, height adjustable, computer tablet with digital health apps (TinyTablet)	Communication and cognitive training performed in standing or sitting	Tiny Tablet, UK
H-Man robotic arm rehabilitation device	Upper limb training and cognitive training	Articares, Singapore
Roylan Semi-Circular Peg Board	Upper limb training	Performance Health, UK

Although the DAIM intensity tracker focuses on lower-limb rehabilitation, the dosage tracker was designed to be adaptable across all domains of stroke therapy, including upper-limb, cognitive, and speech-based interventions. The decision to test the system in this broader context reflects the aim of assessing its feasibility across the full range of rehabilitation activities. Whereas the previous study examined the tracker's performance during treadmill-based lower-limb sessions, this investigation expands its scope to ensure the system is applicable to the wider rehabilitation landscape. These insights will be particularly valuable when planning future implementation studies in clinical settings that span multiple therapy types.

4.4.3.3. Ethics

This study received ethical approval from the Strathclyde University Ethics Committee under the protocol number UEC20/08: Kerr: Generic Framework Application: User experience of a technology-based rehabilitation programme, Appendix 13. All participants provided informed consent prior to their involvement in the study.

4.4.3.4. Analysis

The data gathered from the SUS and IMI surveys were analysed to determine the usability and accuracy of the digital dosage tracking system. The SUS provided a quantitative measure of usability, and the IMI offered insights into the participants' motivation and engagement with the system. Whereas the quantitative duration data could validate the hardware and software of the system, effectively addressing all design considerations to meet the co-design standards and adhering to the MRC's framework 'feasibility' stage, and to help with the generation of the next prototype iteration. The results were used to evaluate the trackers potential for integration into clinical practice.

4.4.3.5. Data Collection and Management – Dosage tracker

Participants UID, Activity name, Duration (HH:MM:SS) and a timestamp of when the data was taken was collected digitally from the system every time a user would 'tap out' of a rehabilitation device. This data was collected to use as a comparative to the standard manual tracking of the user's time in the cohort. All five boxes were placed in the room with one box assigned to log the time a participant spent in the room overall and record how regular a user was visiting the cohort every week. Box 2-5 were assigned to different rehabilitative devices. It is important to note that similar to the previous study and as per the current design iteration a computer had to be running throughout the duration of each session, this computer would act as the 'central hub' for the system and could facilitate all data requests sent to and from the NFC device using the local Wi-Fi network situated within the TERG.

From the results of the previous study, each participant was given a white plastic card when introduced to the system, each containing its' own unique identification number (UID). A white adhesive label was also placed on the top over the card that had their given participant number (as per the requirements of participating in the cohort programme) that could be removed at the end of the programme to be used again. Participants would leave their cards in a secured location within the locked rehabilitative room at the end of every session and retrieve their card when entering. This was to minimise the chance of damage or loss of the card which would result in delays or lack of data collection; however, it should be noted that the finalised prototype iteration would result in a user having a card that they may permanently keep. Volunteers and staff members were still required to manually complete their standard daily data collection sheets throughout the entire cohort duration which were kept in a locked filing cabinet.

In coherence with the previous study, all data was immediately stored as a CSV file on the core password-protected computer from which the flask server is running from and after each session, was moved to a password-protected Microsoft OneDrive folder (Microsoft Office, 2024), accessible only to the investigator and supervisor.

4.4.3.6. Data Collection and Management – SUS and Adapted IMI

The IMI is a multidimensional survey based in Self-Determination theory and is designed to assess a user's subjective experience and motivation when engaging in an activity (Appendix 9) (Matamala-Gomez et al., 2020; Ryan & Deci, 1994). Unlike the SUS which focuses on the system's performance and ease of use, this survey evaluates how engaging and motivating the experience is for the end-user. Additionally, whilst you can produce one overall IMI score, the survey also creates various subscale scores including interest/ enjoyment, perceived competence, perceived choice, and pressure/tension in its standard version.

The standard IMI comprises approximately 20 statements to which participants respond using a 7-point Likert scale ranging from 1 (not true at all) to 7 (very true). Some statements are negatively phrased to reduce response bias, and these negatively worded items must be reverse scored before calculating the final scores (Deci, 1985). In practice, for each item, the response is transformed so that all items are scored in the same direction. For non-reversed items the transformation is given by:

$$s_i = r_i$$

and for reversed items by:

$$s_i = 8 - r_i$$

where r_i is the response for item i. Once each item's response is transformed, the score for a given subscale that includes n items is calculated as the mean of the transformed item scores:

$$Subscale\ Score = \frac{1}{n}\sum_{i=1}^{n} s_i$$

For example, if a subscale consists of four items where items 2 and 4 are reversed, the subscale score would be calculated as:

$$Subscale\ Score = \frac{1}{4}\left(r_1 + (8 - r_2) + r_3 + (8 - r_4)\right)$$

Across literature, for all subscales, the standard perception of a 'high' score sits above 5, with a 'moderate' score between 4 and 5 and a 'low' score sitting at less than 3 (Jawaid et al., 2024; Knippenberg et al., 2021; Thoma et al., 2015). It is important, however, to stress that a 'high' IMI score does not indicate a successful system, for example a high IMI score applied to the 'Emotional Pressure/Tension' subscale within the IMI would indicate that the person felt very pressured, anxious, or stressed while performing the activity. Whereas a high IMI score for the subscale 'Perceived Choice' would indicate a strong sense of autonomy in that the participant

felt the activity was fully voluntary and self-directed. Therefore, it is important to consider scores separately rather than combined, with researchers often looking for a (Reyes et al., 2021) (Table 13).

Table 13 IMI (20-item version) subscales (Deci, 1985).

Dimension	Items	Number of Items
Interest/Enjoyment	1, 5(R), 10(R), 13	4
Perceived Competence	2, 15, 18(R)	3
Effort/Importance	3, 8(R), 16	3
Pressure/Tension	4(R), 11, 19	3
Perceived Choice	7, 12(R), 17	3
Value/Usefulness	6, 9, 14, 20	4

In rehabilitation technology, participant motivation has often been linked to successful outcomes and so the IMI has been extensively used in the development of gamified rehabilitation and digital health (Korn & Tietz, 2017; Matamala-Gomez et al., 2020; Pearce et al., 2023; Zlotnik et al., 2023). One systematic review even noted that the IMI is amongst the most commonly used tools to assess patient motivation in technology-assisted rehabilitation, and recommended its use for evaluating engagement (Monardo et al., 2021). The IMI is also considered a reliable assessment (intraclass correlation = .70 in healthcare settings) (Tsigilis & Theodosiou, 2003). Therefore, the IMI can demonstrate that the co-design approach created a system that was motivating to its intended users, thereby promoting long-term adherence to their rehabilitation goals.

As per the data management of the previous study, the collected survey results were manually inputted into a Microsoft Excel 2016 (Microsoft Office, 2024) document which was stored on a password-protected Microsoft OneDrive folder (Microsoft Office, 2024). Subsequently the physical copies of the results were then stored in a locked filing cabinet. Both SUS and adapted IMI templates are shown in Appendix 9.

4.4.4. Results

A total of 9 people participated in this study (Table 14); however, 2 participants decided to withdraw from the trial in the final week, 1 due to other commitments and the second due to short-term illness. High usability was demonstrated with a mean IMI score of 6.29/7 (SD 1.5; Table 15), and a mean SUS score of 91.43/100 (SD 9.53, Table 16); the total SUS score was calculated based on participants' responses to the 10-item questionnaire, with each item rated on a 5-point Likert scale. The scores were normalized and converted to a range of 0-100.

Table 14 Participant characteristics of usability trial.

Characteristics	**All Participants (n=9)**
Age (years), mean (SD)	62.56 (10.32)
Gender (male/female)	5/1
Aphasia (aphasic/non-aphasic)	2/4
Living Situation (live with family/live alone)	4/2
Hemiplegic Side (left/right/both)	7/1/1
Time Since Stroke (months), mean (SD)	50.6 (21.74)

Table 15 Collective adaptive Intrinsic Motivation Inventory results with averages.

Question	P1	P2	P3	P4	P5	P6	P7	Mean (SD)
1. I enjoyed using this system very much.	7	7	7	6	7	6	6	6.57 (0.53)
2. I think I am pretty good at using this system.	6	7	7	1	6	5	6	5.43 (2.07)
3. I put a lot of effort into using this system.	6	6	7	3	7	6	6	5.86 (1.35)
4. I did not feel nervous at all whilst using it.	7	7	7	7	4	4	4	5.71 (1.60)
5. I thought using this system was a boring. (R)[a]	7	7	7	7	7	6	7	6.86 (0.38)
6. I believe this system could be of some value to me.	6	7	7	2	7	6	7	6 (1.83)
7. I believe I had some choice about using this system.	7	7	7	3	6	6	6	6 (1.41)
8. I didn't try very hard to do well at using the system. (R)	7	7	7	7	6	5	2	5.86 (1.86)
9. I think that using this system is useful for tracking my rehabilitation exercises.	7	7	7	7	6	6	7	6.71 (0.49)
10. This system did not hold my attention at all. (R)	7	7	7	7	7	6	7	6.86 (0.38)
11. I felt very tense whilst using the system.	1	1	1	1	4	4	1	1.86 (1.46)
12. I felt like it was not my own choice to do this task. (R)	7	7	7	7	4	4	4	5.71 (1.60)
13. I thought this system was quite enjoyable	6	7	7	7	6	6	7	6.57 (0.53)
14. I would be willing to use this again because it has some value to me.	7	7	7	7	6	6	7	6.71 (0.49)
15. I am satisfied with my performance at using the system.	6	7	7	7	5	5	6	6.14 (0.90)
16. It was important to me to do well at using the system.	6	6	7	6	5	5	6	5.86 (0.69)
17. I used this system because I wanted to.	6	7	7	6	6	6	7	6.43 (0.53)
18. Using the system was an activity that I couldn’t do very well. (R)	7	7	7	7	7	6	7	6.86 (0.38)
19. I felt pressured while doing this.	1	1	1	1	1	2	1	1.14 (0.38)

20. I think doing this activity could help me to motivate myself in continuing my rehabilitation.	7	7	7	7	7	6	7	6.86 (0.38)

[a]R: reverse scored.

Table 16 System Usability Scale questions with average results; each item was rated on a 5-point Likert scale.

Question	Mean (SD)
1. I think I would like to use this system frequently in the cohort.	4 (0)
2. I found the system unnecessarily complex.	3.86 (0.35)
3. I thought the system was easy to use.	3.71 (0.45)
4. I think that I would need the support of a technical person to be able to use this system.	2.71 (1.75)
5. I found the various functions in this system were well integrated.	3.57 (0.49)
6. I thought there was too much inconsistency in this system.	3.57 (0.49)
7. I would imagine that most people would learn to use this system very quickly.	3.86 (0.35)
8. I found the tool very cumbersome to use.	3.57 (0.73)
9. I felt very confident using the system.	3.86 (0.35)
10. I needed to learn a lot of things before I could get going with this system.	3.86 (0.35)

4.4.4.1. Statistical Analysis

A paired t-test was used to examine whether the DAIM system produced systematically different mean rehabilitation times compared to manual recording for each activity. While this test can identify differences in group-level averages, it does not assess agreement between individual measurements. A p-value below 0.05 was interpreted as evidence of a significant difference in means, but agreement between methods was evaluated separately using Bland-Altman analysis.

Cohen's D was calculated to evaluate the practical significance of the differences observed. This effect size metric is derived by dividing the mean difference by the standard deviation of the differences. Interpretations follow standard thresholds: approximately 0.2 is considered a small effect, 0.5 medium, and 0.8 or greater is large. Reporting both p-values and effect sizes provides a more complete picture of both statistical and clinical relevance.

Table 17 presents the t-test and effect size results across individual devices and for all devices collectively.

Table 17: Summary of statistical outcomes for time recording comparisons across individual devices and the collective.

Activity	t Stat	Two-tailed P value	P Significance	Cohen's D	Effect Size
H MAN (Articares, Singapore)	-3.090	0.018	Significant	-0.809	Large
Armeo®Spring (Hocoma, Switzerland)	1.195	0.286	Not significant	0.549	Medium
TinyTablet (Tiny Tablet, UK)	0.281	0.790	Not significant	0.141	Small
Roylan Pegboard (Performance Health, UK|)	-1.614	0.182	Not significant	-0.239	Small
Gripable (GripAble, UK)	-0.629	0.574	Not significant	-0.519	Medium
All Devices	-0.299	0.767	Not significant	-0.050	Negligible

Across all devices with complete data (n=29), the mean session duration logged by the DAIM system was 0.0121 (hours), compared to 0.0125 (hours) for manual logging. The paired t-test showed no statistically significant difference between the two methods (p=0.767), and the effect size (Cohen's D=-0.050) was negligible, indicating no systematic difference in mean session durations at the group level.

Out of the 44 rehabilitation exercises recorded during the study, 29 activities (65.9%) were captured by both the DAIM system and manual logging, forming the complete dataset used for paired t-test and Bland-Altman analyses. The remaining 15 activities (34.1%) were only recorded by the system, reflecting instances where manual logging was incomplete or omitted. Figure 27 presents a Bland-Altman plot comparing complete system-recorded and manually recorded durations.

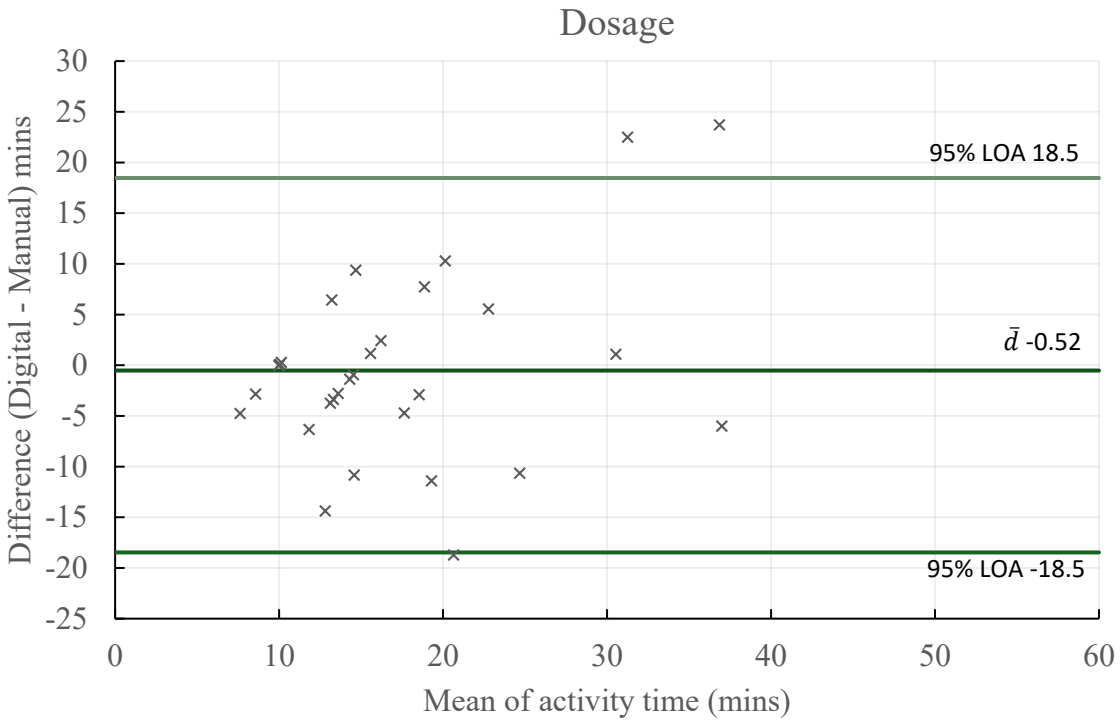


Figure 28 Bland-Altman plot comparing digital and manual dosage tracking methods. This plot shows the difference between the digital and manual dosage tracking methods for all recorded activities (n=29) at the TERG, plotted against the mean activity time. The plot includes the mean difference (bias, d-) and the upper and lower limits of agreement at a 95% CI. The bias value, closely aligned with the x=0 axis, indicates a good degree of validity between the 2 methods. LOA: limit of agreement.

4.4.5. Discussion

This study's outcomes demonstrated the device's clear usability among users. The high scores for SUS and IMI were not surprising given the preceding co-creation process. Usability is a critical factor in health care and rehabilitation settings, as it directly influences the likelihood

of a device being adopted in routine practice. The high usability demonstrated by this digital dose tracker ensures that both health care providers and people with stroke history can integrate the device into daily operations without significant disruptions or extensive training. This ease of use supports seamless implementation in clinical environments, enhancing the overall user experience and increasing the likelihood of widespread adoption (Carayon & Hoonakker, 2019). In rehabilitation, where consistent and accurate use of technology can significantly impact patient outcomes and care efficiency, high usability is particularly important (Staggers & Troseth, 2011).

Throughout the trial participants were allowed to give feedback about the device to allow for adjustment and modifications, this included adjusting the brightness of the LEDs and increasing the volume of the speaker to improve audio and visual feedback. The device is limited in the quality of its components due to funding however if additional funding were to be obtained this would contribute to the refinement of the trackers to reduce the size and thus improve portability.

The results of this investigation provided a picture of the differences between the two recording methods. In interpreting the results of this investigation, it is important to acknowledge the variability in the volume of comparable data sets across different rehabilitation activities. This disparity is largely due to the participant-driven nature of the activity selection process within the TERG programme. Given that participants have the autonomy to choose the rehabilitation devices and exercises they prefer, it is natural that some devices are favoured over others. This selection bias reflects the individual preferences and motivations of the participants, which can influence the frequency and duration of use for each device. Consequently, this results in a diverse range of data availability, with some devices accumulating more usage data than others. Such variations in data volume must be considered when evaluating the efficiency and

effectiveness of each device, as they can affect the robustness of statistical comparisons and the interpretation of the system's relative performance.

The combined analysis across all rehabilitation devices showed no significant mean difference between the DAIM system and manual recording when complete data were available. The negligible effect size (Cohen's D=-0.050) further suggests that there is no systematic bias or large-scale divergence between the two methods at the group level. However, it is important to acknowledge the inherent limitations of the paired t-test used in this analysis. As a parametric test, the paired t-test is designed to detect differences between means rather than assessing the degree of agreement or interchangeability between individual measurements (Giavarina, 2015; Martin Bland & Altman, 1986). A non-significant p-value indicates only that there is insufficient evidence to conclude the means differ, but it does not statistically confirm that the two methods produce identical results for every session (Kozak & Piepho, 2018).

To move beyond the assessment of mean differences, the Bland-Altman plot was employed. This approach is more appropriate for assessing agreement, as it shows the distribution of individual differences across the range of measurements. The plot reinforced the t-test findings by showing a varied distribution of DAIM-recorded times, suggesting the automated system is capturing a more accurate representation of the true variability in rehabilitation sessions.

A noteworthy finding was the substantial proportion of exercises (34.1%) that lacked manual logging entirely. The discrepancies observed between the DAIM system and manual recordings, characterised by a mean difference of 0.52 minutes but a larger standard deviation of 10.92 minutes, are primarily attributed to the inherent variability and inaccuracies of manual logging in a busy clinical environment. These differences likely stem from variations in individual therapist recording practices and the tendency to provide "rough estimates" of time spent at a station rather than precise durations. Despite these known flaws, the use of manual

logs as a comparative baseline is justified as they represent the current established clinical standard for auditing and developing stroke care pathways. Manual recording provides an ecologically valid benchmark of "accepted practice," where therapists traditionally log total time without distinguishing between active therapy and brief pauses. By demonstrating that the digital tracker aligns with this accepted clinical margin while offering a broader, more consistent scope of data, the system is validated against the very real-world standards it is designed to enhance.

The Bland-Altman plot reinforced this by showing a varied distribution of DAIM-recorded times, suggesting the automated system is capturing a more accurate representation of the true variability in rehabilitation sessions. These findings further demonstrate the system's ability to provide a more accurate and unbiased assessment of rehabilitation activity, offering substantial advantages over traditional manual methods.

4.4.5.1. Participant Feedback

An interesting pattern of behaviour emerged midway through the programme, notably around week four, involving informal self-competition among two participants. This behaviour was particularly evident across four rehabilitation activities: TinyTablet, Pegboard, Gripable, and H-Man. One participant began setting personal challenges, such as timing how long they could stand while using the TinyTablet before needing to sit and tracking the duration required to complete a specific Gripable game. Similarly, a second participant created benchmarks for themselves by timing how quickly they could achieve specific goals.

Additionally, another participant noted that observing others' logged performance times fostered a desire to enhance their own efforts and match or surpass peer achievements. Although the primary aim of this thesis was to foster collaborative rather than competitive rehabilitation, the spontaneous emergence of these self-driven challenges and peer-influenced

motivation highlights the unintended, yet potentially beneficial, outcomes of incorporating real-time progress tracking into rehabilitation sessions. This experience suggests that logging not only provides documentation of progress but also serves to heighten engagement. Therefore, future iterations of the DAIM system considered these motivational aspects more explicitly, recognising that performance tracking could foster a positive and motivational environment, increasing user engagement and promoting high useability of the DAIM.

4.4.5.2. Prototype enhancements following feedback

Participant feedback was continuously recorded throughout the 8-week investigation in a dedicated logbook stored within the upper-limb rehabilitation area of the TERG. Early feedback, particularly from the first four weeks, highlighted two significant design concerns: participants had difficulty clearly hearing the audio feedback when scanning their NFC cards, and they desired improved visual confirmation that their interactions with the device were successful. Originally, the NFC reader's feedback was indicated by a small 8-ohm speaker and a subtle LED on the Arduino Nano 33 IoT, which was difficult to perceive as it was only visible through the Micro USB port (Section 4.2.1).

To address these concerns promptly, all five dosage trackers underwent several modifications. Each device received an upgraded dual-LED system designed to offer immediate visual confirmation: a green LED signifying successful card scans (one flash for login, two flashes for logout) and a red LED indicating an error through three rapid flashes. These visual signals were complemented by distinct audio tones. The speaker was upgraded to a 1.5W, 8-ohm loudspeaker and calibrated to maximum volume, ensuring audio feedback was clearly discernible during device operation. Furthermore, physical design alterations were made to enhance sensory output; three strategically positioned 5mm diameter holes were drilled into the top and back of each tracker enclosure, amplifying internal LED visibility and allowing clearer sound and LED projection.

Additionally, power source optimisation was carried out following observations regarding the limited two-week lifespan of the original 9V lithium-ion batteries. Each tracker was subsequently fitted with a rechargeable 5V, 1A power bank, providing consistent and reliable power while significantly reducing replacement frequency, cost, and environmental waste.

The revised tracker configuration comprised the Arduino Nano 33 IoT (SAMD21; Arduino, Italy), a PN532 NFC module (NXP Semiconductors, Netherlands), enhanced audio and visual feedback components, and the rechargeable power supply. Operationally, an initial NFC card scan produced a single green LED flash and an audio tone to indicate successful scan-in, while a second scan generated a double green LED flash and confirmation tone to indicate successful scan-out (Figure 29). Additionally, yellow visual indicators were added to the device casing to clearly denote the location of the NFC reader, thereby reducing scanning errors and improving overall ease of use (Figure 30).

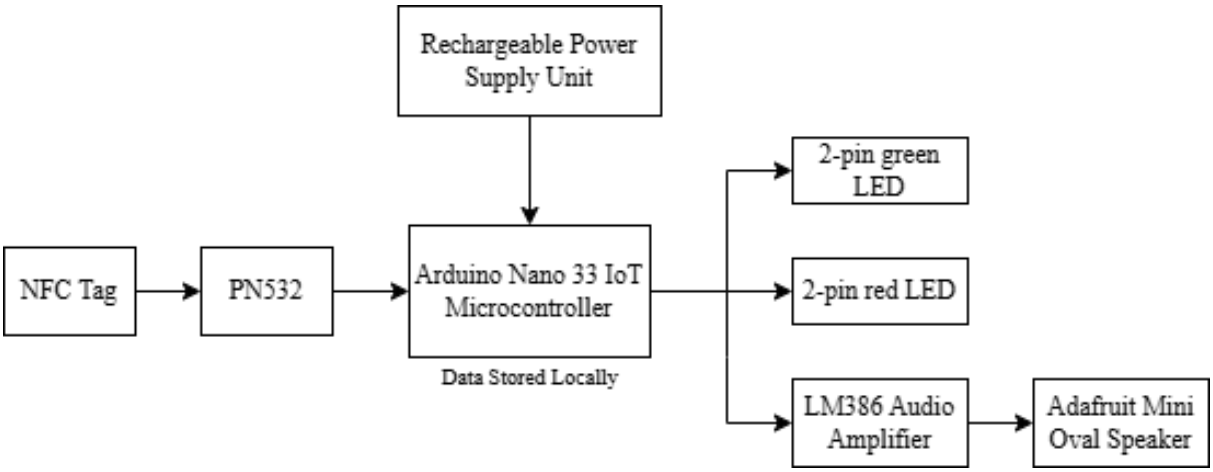


Figure 29 System block diagram. IoT: Internet of Things; NFC: Near-Field Communication.

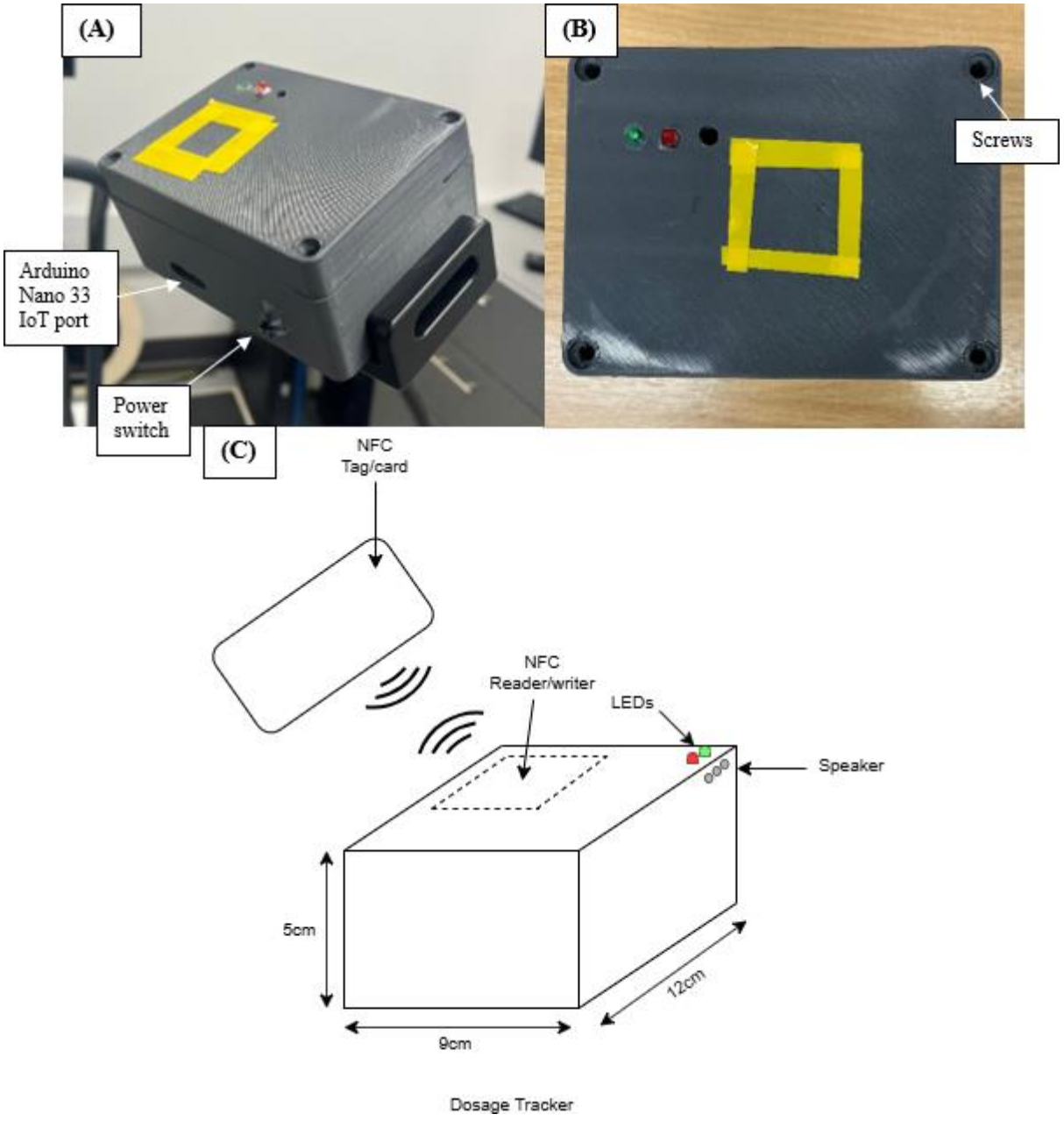


Figure 30 Photographs and diagram of the updated NFC dosage tracker. (A) Overall view of the tracker, (B) top-down view, and (C) diagram illustrating key components and functionality. The diagram highlights the positions of the light-emitting diodes the device to facilitate communication between the card and the reader for logging participant dosage. The yellow markings in (A) and (B) serve as visual guides to indicate the precise location of the NFC reader, minimising scanning errors.

The next phase of the project will investigate the implementation of the digital dosage tracking system within a clinical rehabilitation setting, specifically evaluating its effectiveness in accurately monitoring acute and sub-acute stroke rehabilitation sessions.

4.5. Tracking Rehabilitation Dosage in a Hospital Environment After Stroke: Validity and Feasibility Study

A previous version of this study has been published in JMIR Rehabilitation and Assistive Technologies (Boyd et al., 2025).

4.5.1. Introduction

With the successful completion of prototype testing in a research gym setting with chronic stroke participants (Section 4.4) , this next study involved a clinical trial of the trackers' feasibility and validity The primary outcomes for were dose validity (comparison with the current method) and tracker feasibility (2024). Feasibility was defined as the ability of the digital dose tracker to be effectively used by all participants, including those with cognitive or physical impairments, without requiring significant modifications or support. It was assessed by the absence of user errors, withdrawals, and the successful capture of accurate rehabilitation data across various activities (Kerr et al., 2023).

4.5.2. Methods

4.5.2.1. Participants

In-patients at a local NHS hospital, with a diagnosis of stroke and referred for rehabilitation, were invited to participate in the study, provided they met the following inclusion criteria: diagnosis of a new stroke by an NHS Lanarkshire physician, more than 48 hours since the stroke event, medically fit for rehabilitation as determined by medical staff, deemed to require rehabilitation, and able to provide informed consent. Individuals were excluded if they were acutely medically unwell, had active cardiac disease (such as unstable angina), active delirium or significant levels of confusion, had a seizure within the past 7 days, were being managed under the Adults with Incapacity Act, or were known to be pregnant. Those with aphasia and

other cognitive or communicative difficulties resulting from their strokes were not excluded from participating. Given the nature of the stroke population, a significant proportion of participants were likely to have these impairments. In the UK, it is estimated that 50% of stroke survivors experience cognitive impairment, and approximately one-third have aphasia or other communication difficulties, particularly in the acute and sub-acute phases of recovery (Stroke Association, 2025).

4.5.2.2. Testing

Participants attended as many sessions at a rehabilitation gym located on the stroke ward as able, with sessions lasting up to 2 hours. The tracker recorded the start and stop times when a participant scans their card at each activity, providing a log of the total time spent at each activity, the person who used it and exactly what the activity was to a local database based within the ward. At the same time, two supervising clinical staff observed all participants and manually recorded the rehabilitation activities and durations. This manual logging was intended to simulate typical clinical practice, based on the advice of the local rehabilitation team, where therapists record the time spent at each station or device without tracking finer details such as repetitions or specific exercises.

4.5.2.3. Ethical Considerations

All participants provided informed consent before their involvement in the study. Participants did not receive compensation, and all data were anonymized. The study was part of a clinical trial (ClinicalTrials.gov; NCT05981729) and received NHS Research & Development ethical approval from South East Scotland Research Ethics Committee 1 (IRAS ID No. 329156, Appendix 13).

4.5.2.4. Analysis

To assess the equivalence of the digital dosage tracking system with manual recording methods, paired sample *t* tests were used to compare the mean times recorded by the 2 methods for each activity. Cohen *d* was calculated to quantify the effect sizes of any observed differences, with small effect sizes being indicative of negligible differences. Bland-Altman plots were used to visually explore the relationship between the 2 methods, and the limits of agreement (LOA) were calculated with a 95% CI to determine the range within which most differences would fall. Time recordings were standardised to minutes, and the average absolute time discrepancies and their variability are presented in the Results section. An acceptable range for discrepancies was decided to be within ±5%.

4.5.3. Results

Throughout the 6-month duration, 27 participants were recruited and completed the study (Table 18). Across the 27 participants, 235 activities were recorded by both digital and manual methods with an average number of sessions during inpatient stay of 9.1 (SD 7.4). The paired t-test indicated no statistically significant difference between the digital and manual recordings ($t_{235}=-0.73$; $p=.47$; Cohen $d=-0.03$), suggesting that the two methods did not differ systematically in mean session duration at the group level. The overall analysis, encompassing all recorded data from the various rehabilitation stations and gym attendance, revealed an average absolute mean time difference of 0.52 (SD 10.92) minutes across 235 total uses. This absolute mean time difference reflects a small 1-2-minute difference between the digital and manual recorded times, indicating that whilst minor differences existed, they were not systematic and likely stemmed from normal variations in manual documentation.

Table 18 Participant characteristics of feasibility and validity trial.

Characteristics	All Participants (n=27)
Age (years), mean (SD)	68.62 (13.89)
Gender (male/female)	13/14
Stroke type (ischemic/haemorrhagic)	25/2
Time since stroke (days), mean (SD)	17.76 (13.55)

The Bland-Altman plot (Figure 31) shows an even spread across the range of activity durations, indicating consistent agreement between the digital tracker and manual recordings. The plot reveals a bias of −1.23 minutes, suggesting good accuracy of the digital tracker relative to the manual method, with only a small systematic bias. The LOA were calculated to be from −21.59 to 21.59 minutes, which encompasses most of the observed discrepancies. Despite this range, the review of activity-specific durations revealed only minor differences, no greater than 6 minutes on average (Table 19), further supporting the reliability of the digital tracking system.

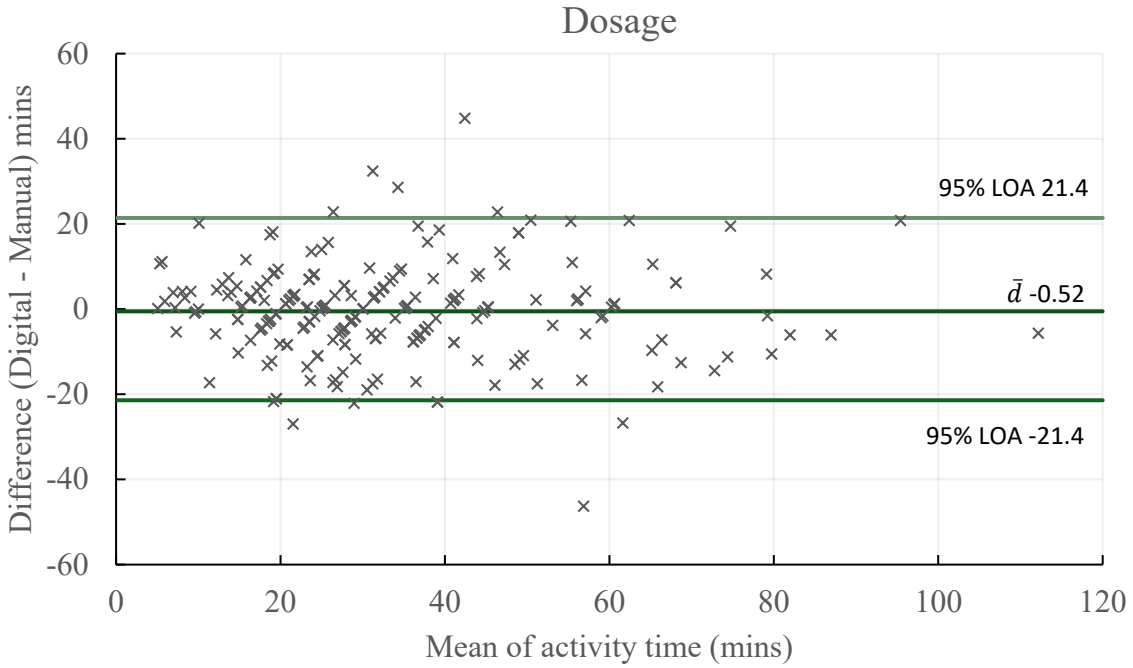


Figure 31 Bland-Altman plot comparing digital and manual dosage tracking methods. This plot shows the difference between the digital and manual dosage tracking methods for all recorded activities (n=235) at the stroke ward, plotted against the mean activity time. The plot

includes the mean difference (bias, d-) and the upper and lower limits of agreement at a 95% CI. The bias value, closely aligned with the x=0 axis, indicates a high degree of validity between the 2 methods. LOA: limit of agreement.

Table 19 Summary of rehabilitation workstations, mean time of use, and difference between digital and manual recordings. This table presents the number of uses and equipment for each workstation, the mean time of use (minutes, SD) based on manual recordings (the current standard within the NHS), and the average difference (minutes, mean ± SD) between digital tracker recordings and manual recordings. The "overall" row shows combined data across all workstations and gym attendance.

Workstation Category	Equipment	Number of Uses (n)	Mean Time of Use (minutes, (SD))	Mean Time Difference of Digital vs Manual (minutes, (SD))
Upper Limb Station	Graded Repetitive Arm Supplementary Programme (GRASP) kits (Neuroquip, UK), Gripable	28	31.63 (15.12)	4.73 (12.60)
Cognitive Applications	TinyTablet (Tiny Tablet, UK)	27	24.45 (10.92)	2.10 (6.65)
Speech Applications	TinyTablet (Tiny Tablet, UK)	4	36.25 (26.32)	2.43 (11.07)
Power Assist Equipment	Cross cycle, Chest & Legs, and Seated Climber devices (Innerva, UK)	74	22.60 (12.40)	3.98 (10.08)
All Equipment Uses	All above-listed equipment (excluding gym attendance)	133	25.27 (13.88)	0.87 (10.75)
Total Time Spent in Rehabilitation Gym	Attendance in gym	102	43.95 (19.42)	3.58 (14.08)
Overall	-[a]	**235**	**33.40 (18.95)**	**0.52 (10.92)**

[a] Not applicable.

4.5.4. Discussion

The aim of this study was to evaluate a novel digital dose tracker against the standard manual recording method in a clinical setting. The Bland-Altman results showed a high level of agreement between the digital and manual methods, with Cohen d indicating a negligible effect size, which suggests that the differences between the 2 methods are minimal. This result confirms the digital tracker's consistent and complete data capture. Manual recording is currently the method used for auditing and developing stroke care pathways (NHS England National service model, 2022). The digital tracker's ability to collect a broader range of activity data, as shown in Figure 31, highlights its potential to describe the intervention in greater detail, benefiting health care providers attempting to improve their services and researchers aiming to better understand response to rehabilitation interventions.

Whilst the mean time difference between the digital and manual methods is relatively small (0.52 min), the larger SD 10.92 min indicates some variability in individual time recordings. This variability could be attributed to factors such as differences in manual recording practices among therapists, variations in task complexity, and individual participant behaviour during rehabilitation sessions. Despite this variability, the overall agreement between the 2 methods remains strong, suggesting that the digital system is a valid tool for tracking rehabilitation dosage, especially when considering the average results across multiple sessions and participants.

The digital tracker accurately tracked rehabilitation activities by logging the unique identifiers of both participants and devices, ensuring precise data collection. Conducted under direct observation, therapists manually recorded the time spent at each station, reflecting standard clinical practice. Whilst a minor average difference of about 1 minute was noted between the

digital system and manual recordings, this difference was minimal and fell within an acceptable range.

In line with the definition of rehabilitation dosage, which includes the intensity, frequency, and duration of rehabilitation activities, the digital tracker successfully captures the essential elements of dosage as required by this definition. Although intensity refers to the individualised adjustment of daily therapy across various domains such as physiotherapy, occupational therapy, and speech therapy, this tracker is particularly adept at accurately recording the frequency and duration of therapy sessions. By logging the start and stop times of each session, the tracker provides a measure of the total duration of rehab, which is critical for ensuring that people with stroke history receive the appropriate amount of therapy prescribed to them and can be used to monitor achievement of guidelines.

The digital trackers approach to tracking rehabilitation dosage mirrors the standard clinical practice where therapists estimate the total time a patient spends at a therapy station. Therapists typically log this time without distinguishing between active therapy and brief pauses, which has been an accepted method in clinical practice for years. The 1-minute average difference observed between the therapists' manual logs and the digital recordings reflects the minor variations inherent in manual estimation. Importantly, the fact that these times align so closely and fall within clinically acceptable margins of error demonstrates that this method does not negatively affect the results. This small difference is within the clinically acceptable range, reinforcing the digital trackers reliability as a tool for tracking rehabilitation dosage.

The distribution of attendance across the different rehabilitation workstations also provides insight into the priorities and preferences of people with stroke history during their rehabilitation. Users at the stroke ward's rehabilitation gym had the autonomy to select the rehabilitation they preferred, with guidance and supervision, during their sessions. The Power

Assisted Equipment station had the highest number of uses (n=74) which may reflect a common patient priority of focusing on motor recovery (Rudberg et al., 2021). This preference is often driven by the desire to regain physical independence, which has been previously recognized as a priority for individuals with stroke over cognitive or speech rehabilitation.

The Bland-Altman plot, Figure 31, showed that the device was accurate in depicting a user's rehabilitation journey and the LOA were calculated with a 95% CI. There is currently no clinical documentation which specifies an acceptable LOA, but a margin of error within ±5%-10% was deemed acceptable, given that manual recording in rehabilitation contexts could vary widely, affecting the reliability of data (Zanier et al., 2007). The LOA determined in this study was within this range.

Table 19 shows that all rehabilitation workstations had an average time difference of just under 5 minutes. This difference is attributed to the need for hoist or transfer assistance for users with low to no mobility, resulting in waiting periods. This also applies to the time taken for participants to transfer in and out of the rehabilitation gym. Overall, wide differences were rare, and outliers were attributed to instances of human error in the manual recordings when the therapist was observing and recording multiple participants at once.

The feasibility of the digital dose tracker was further demonstrated by the fact that all users of the stroke ward, regardless of their varying levels of cognitive or physical impairment, were able to effectively use the system. There were no withdrawals or errors recorded by the tracker during the study, nor were any observed by the 2 clinical staff, demonstrating the trackers accessibility and functionality across a diverse stroke population.

The study faced challenges related to the rate of participant uptake. A significant number of potential participants could not be included because they were only in the hospital for a few days, which did not allow sufficient time for the consent process. In addition, the rate of uptake

in the study and the number of viable participants varied depending on the number of people admitted to the stroke ward during the study period. This limitation reduced the overall sample size, impacting the generalizability of the findings. Future studies could consider running for a longer duration to accommodate the consent process and variations inpatient admissions, thereby ensuring a more comprehensive assessment of rehabilitation dosage.

4.5.5. Conclusion

This study has evaluated a novel, co-designed, digital system for monitoring rehabilitation dose finding it largely agreed with traditional manual methods. It is one of the first studies to implement such a method of rehabilitation dosage tracking in a clinical rehabilitation setting. This promising system has the capacity to provide an accurate and automated method for measuring achievement of the new National Clinical Guidelines for Stroke recommendations and providing practical support for therapists and researchers.

4.6. Chapter Summary

This chapter presented the full design, development, and evaluation of the digital dosage tracking component of the DAIM system. Developed in response to a lack of standardised and accurate methods for tracking rehabilitation duration and frequency, the dosage tracker was designed using NFC-enabled Arduino components and shaped through stakeholder-led requirements established in Chapter 3. The system aimed to offer an automated, low-cost, and user-friendly solution for capturing daily rehabilitation dosage across clinical, research, and home environments. The development process began with the construction of a functional prototype, evaluated through a pilot study with healthy volunteers to establish initial feasibility and accuracy. This was followed by two larger-scale studies conducted in a TERG and a clinical rehabilitation setting involving stroke survivors. These studies assessed usability, feasibility,

and validity in real-world rehabilitation settings and demonstrated the device's compatibility within any existing workflows.

Critically, in the final clinical study, the digital dosage tracker was evaluated against the gold-standard method of manual recording by therapists. It demonstrated strong agreement, with negligible mean differences and limits of agreement that fell within the clinically accepted error range of ±5%–10%. Despite occasional individual variation due to manual recording inconsistency or transfer assistance delays, the tracker proved highly reliable and accurate in capturing rehabilitation sessions across various workstations. These findings position the DAIM dosage tracker as a valid and objective tool for clinical use and capable of supporting stroke care pathways and measuring adherence to national guidelines. Notably, it also recorded a broader scope of activity data than therapists typically documented, adding value for both clinicians and researchers.

Feasibility was reinforced by full user compliance across the diverse stroke population, including those with cognitive and motor impairments, with no errors or withdrawals reported in the final study. Although the study's recruitment was limited by short hospital stays, the system's performance remained robust across all users and settings. These results highlight the tracker's clinical applicability and potential to automate dosage monitoring at scale. Further refinements were also made to the dosage tracker in line with continuous feedback gathered throughout the TERG study in preparation for the clinical study.

Overall, the dosage tracker met and exceeded its core design objectives, showing strong feasibility, validity, and usability across multiple settings. Its development was solidified by participatory co-design and iterative refinement, ensuring it remained aligned with both clinical needs and patient priorities. Having now successfully developed and validated the dosage

tracker; the next stage of the project is to focus on the development of the second core component of the DAIM system: the intensity tracker.

Chapter 5. Design and Development of Intensity Tracking System

5.1. Introduction

As part of the final concept prototype (Chapter 4), the next phase of the development process focused on the iterative design and construction of the wearable intensity tracking system, a critical component of the DAIM system. The DAIM wearable intensity tracker aims objectively measure rehabilitation intensity parameters based on previously established definitions (Section 2.3.2.1), of abnormal movement patterns which can be coupled with dosage tracking parameters, creating detailed report of a person's rehabilitative efforts. This chapter describes the detailed design rationale, including sensor selection, hardware integration, and wearability considerations. Following initial prototype development, a feasibility and validation study was conducted in a TERG. User feedback from these evaluations directly impacted further iterative refinements that would again be presented to stakeholders for feedback.

5.2. Component Selection and Rationale

The codesign focus groups and polls (Chapter 3) were integral in the shaping of the DAIMs system design. Participants were looking for a wearable system that could accurately reflect their rehabilitation efforts, support the tracking of various movement types, and enable effective progress monitoring (Section 3.4.3.1). Poll responses revealed unanimous preference for a wearable worn via a strap or band around the affected limb (Section 3.4.2.5). While preferences regarding the device's visual aesthetics were mixed, there was a slight preference for subtle, understated designs. Participants' views on the importance of aesthetics for

maintaining engagement ranged from ‘neutral’ to ‘extremely important’. Key concerns raised included battery life, the ability to interpret the collected data, and maintaining proper sensor positioning during use (Section 3.4.2.5).

In response to these user insights, the initial concept for the wearable device was developed as a thigh-worn strap integrating a microprocessor capable of detecting lower-limb movements, an LCD screen for real-time visual feedback, and a rechargeable battery. This configuration aimed to directly address both functional requirements and user concerns. With the design direction established in Chapter 3 and the supporting literature gathered in Chapter 2, the next stage involved selecting appropriate hardware components and developing the first working prototype for feasibility testing.

5.2.1. Hardware and Microcontroller Setup

The arguments that led to selecting the Arduino Nano 33 IoT for the dosage tracker (Chapter 4) apply equally to the DAIM intensity unit. First, the intensity tracker must stream high-frequency motion data to the mobile-phone app in real time. The Nano 33 IoT’s on-board BLE radio delivers a stable, low-latency link without extra modules, matching this requirement. Second, at roughly £25 per board, the Nano remains highly cost-effective, allowing several trackers to be built so multiple participants can be instrumented simultaneously during trials. Finally, because the same micro-controller and C/C++ codebase are used in both the dosage and intensity units, the single-developer project avoids the overhead of learning and maintaining multiple tools. This consistency shortens the development timeline and simplifies data integration across DAIM components.

An alternative strategy would have been to adopt a commercial software-development kit (SDK), for example Polar’s SDK for its wrist-worn watches and chest sensors. Those devices are, however, factory-calibrated for trunk or wrist motion and cannot be easily re-tuned for

thigh-mounted, lower-limb kinematics. The co-design focus groups (Section 3.4.2.4) specifically requested a sensor on the hemiplegic limb to capture gait asymmetries; moving the unit to the trunk or wrist would therefore undermine the original design requirements and require renewed stakeholder consultation. Evidence also supports the thigh location: inertial sensors placed on the lower limbs yield more reliable step detection and cadence estimates in stroke survivors, whereas waist-mounted units perform markedly worse because post-stroke trunk kinematics differ from those of healthy gait patterns (Negrini et al., 2020; Van Criekinge et al., 2017). For these technical, economic and user-centred reasons, the Arduino Nano 33 IoT remains the most appropriate microprocessor platform for the DAIM intensity tracker.

A 16 × 2 red, green and blue (RGB) Liquid-crystal display (LCD) with an I²C "back-pack" was selected as the on-board display because it combines clear visual feedback with very low overhead on the micro-controller's pin budget, compatible with both 3.3V and 5V (Figure 32) (ThePiHut, 2025).

Figure 32 Front (above) and back (below) of RGB 16x2 LCD Display (I2C, 3.3V/5V) without I2C "back pack" (ThePiHut, 2025)

Using the I^{2}C backpack, the module needs only 4 wire connections which reduces Arduino overload while already handling a BLE stack and real-time sensor tracking. The I²C can be connected to the Arduino with a short bundle of four pre-crimped Dupont leads, this can be plugged straight from the Nano's headers to the backpack's 4-pin header, avoiding bulky ribbon cables or soldered jumpers that other interfaces would require, thereby simplifying any rapid iterative developments, component replacements or re-routing (Figure 33, Table 20). Arduino coding libraries such as LiquidCrystal_I2C mean the display can be driven with a few lines of firmware, leaving most of the Nano's flash and static random-access memory (SRAM) for the intensity-analysis algorithms.

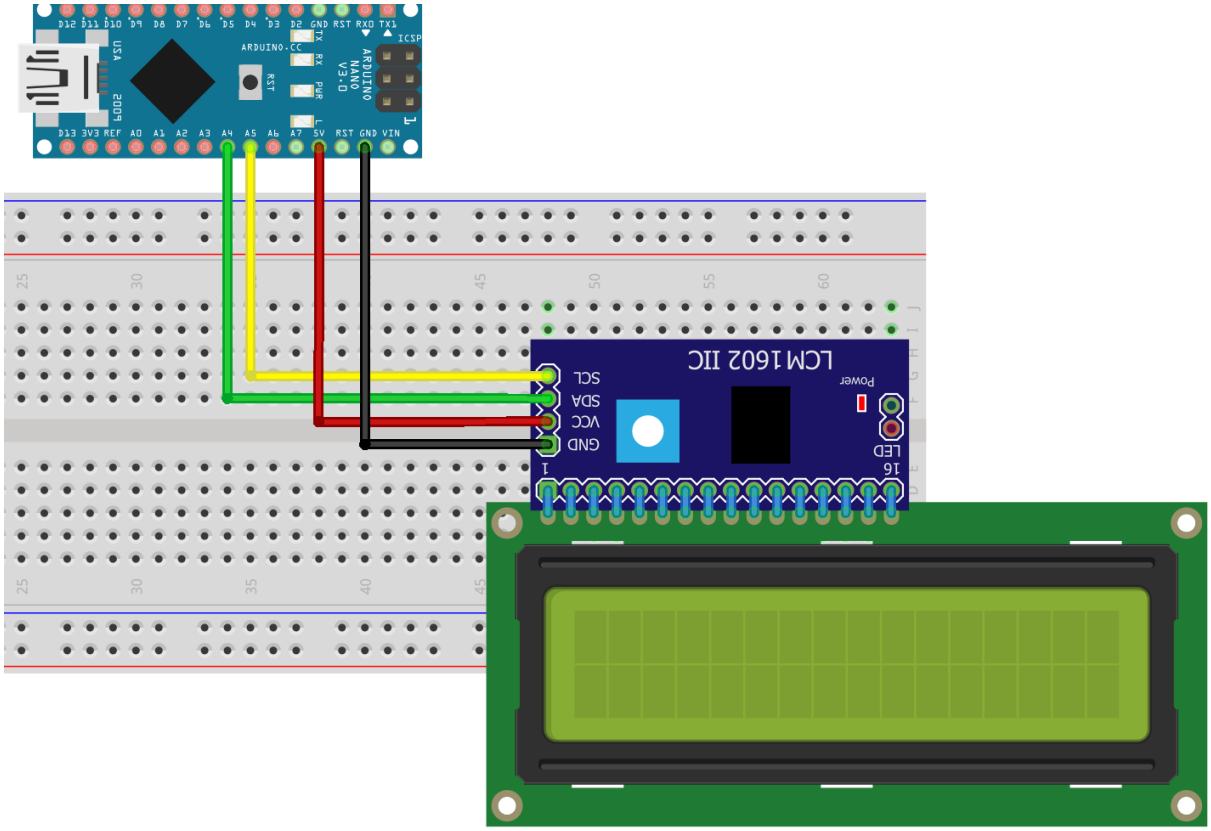


Figure 33 Schematic diagram of an I2C LCD with Arduino Nano 33 IoT.

Table 20 Connection table of LCD with Nano board.

I2C LCD	Arduino Nano
VCC	5V
GND	GND
SDA	A4
SCL	A5

Battery strategy was guided by both stakeholder priorities and lessons learnt from the dosage-tracker trials. During the earlier study disposable 9V cells kept each logger alive for barely a week; replacing every pack soon became the single largest running cost and generated a steady stream of waste batteries, which the focus group had highlighted as a key concern. Switching those loggers to a small power bank eliminated the weekly spend, simplified maintenance for AHPs and volunteers, and offered a modest environmental sustainability gain by cutting single-use cells out of the loop. The same logic was applied to the intensity tracker from the outset.

The Arduino Nano 33 IoT is tolerant of three different supply rails: 3.3V, 5V and the 5V that arrives through its on-board Micro-USB port; it was decided that a commercial 5V, 5000mAh power bank (≈ 10.7 × 3.3 × 3.3 cm, 136 g) could be plugged straight in via a short USB lead. This arrangement lets users' recharge with any standard phone charger, removes the need for a dedicated battery segment, and provides many more hours of use on a single charge. In production the bulky retail pack would be replaced by a slim custom Li-ion pouch and integrated charge-management circuit, trimming both size and weight while retaining the same user-friendly "plug-in overnight" charging routine.

Power-up was kept deliberately simple. The Micro-USB lead remains permanently seated in the Nano 33 IoT, so users activate the tracker simply by inserting the opposite USB-A plug into the power bank and removing the plug turns it off. This "single-motion" start-up was a direct

response to the co-design workshops, where people with stroke (many with hemiparesis or aphasia) asked for a “turn-on-and-go” device that avoided multi-step sequences.

A hardware switch would ultimately be preferable, but at this prototype stage it could not be integrated because the 5V supply enters the board exclusively through the Micro-USB rail, leaving no convenient point to intercept and rout it through a slide-switch or push-button without extensive re-routing of tracks. Future iterations should therefore redesign the power path for example, by introducing an in-line JST connector or a dedicated power-management PCB so that a large, tactile slide-switch can be added while preserving the one-step user experience and reducing wear on the USB socket.

5.2.2. Strap Design

Cost and material availability were key considerations during the component selection process. As the device was intended to be an affordable and scalable solution for end-users, all materials used in its construction needed to align with this low-cost design objective.

To accelerate prototype development and prioritise validation of the Arduino firmware, the design of the thigh strap itself was initially considered a lower priority. While comfort and wearability were important, they could be refined in subsequent iterations. In contrast, failure to meet core performance benchmarks would necessitate a complete system redesign, making firmware accuracy the leading priority in early testing phases

Stakeholder feedback strongly supported the use of a Velcro fastening system over alternatives such as buckles, clips, or magnets. This recommendation was reinforced by existing literature, which notes that approximately 80% of individuals with acute stroke and more than 55% with chronic stroke experience upper limb motor dysfunction. Additionally, around 30% have difficulty with fine motor control (Tang et al., 2024). This significantly limits users’ ability to manipulate small or force-dependent fasteners. Velcro was therefore deemed the most

accessible and practical option, offering ease of use, adjustability, and secure fastening with minimal effort (Karoulla et al., 2024; Zhang et al., 2020). Users would be able to readjust the band at will and use minimal effort to fasten on and remove.

To minimise fabrication time while ensuring ease of use, an off-the-shelf catheter leg strap was repurposed as the base for the wearable intensity tracker. As shown in Figure 34, the strap consists of a lightweight, breathable blend of nylon, polyester, foam, and cotton. It features a blue-edged design with integrated Velcro fastening, allowing for secure and adjustable placement around the user's thigh. The band measures approximately 57.5 cm in length and 4.8 cm in width and accommodates thigh circumferences from 20 cm to 60 cm.

The strap includes two primary regions: a rigid section with small surface Velcro straps, and a flexible Velcro section to adjust the fit with internal silicone ribbing to anchor the band in place. Smaller auxiliary Velcro loops were used to secure the rechargeable battery and Arduino unit during early testing whilst the LCD screen was sewn to the outside of the band (Figure 35).

This approach was meant to maintain stability without compromising on comfort or simplicity, the soft fabric also helped minimise skin irritation during prolonged wear.

Figure 34 Repurposed thigh band

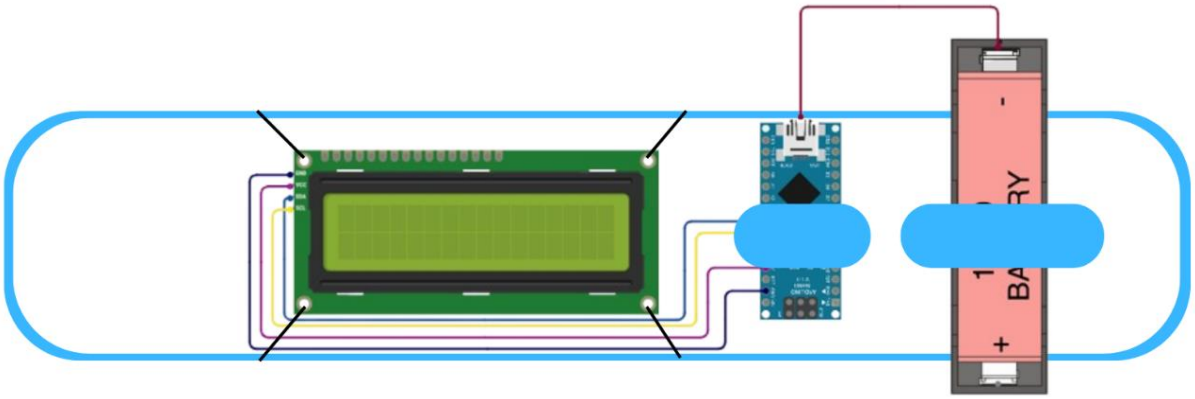


Figure 35 Diagram of proposed first prototype of intensity tracker made on Fritzing (Fritzing, 2025)

5.3. Signal Processing

Firmware was written in C++ (Arduino API, IDE 2.3.2) and organised as a single compilation script (Appendix 5).

5.3.1. Movement Recognition Algorithms

5.3.1.1. Sensor Acquisition and Orientation Estimation

At the start of each main loop iteration, the system queries the IMU using IMU.gyroscopeAvailable(). When this returns true, raw angular velocity data is retrieved at the sensor's nominal 104 Hz sampling rate. For movement analysis, the gyroscope's Y-axis output is used to track pitch motion. Angular velocity in radians per second (ω_y) is converted to degrees per second and used to estimate the pitch angle through numerical integration over time:

$$pitch(t) = pitch(t-1) + \omega_y^{\circ}(t) \cdot \Delta t$$

Here pitch is updated each cycle, assuming most motion occurs in the sagittal plane and that any small gyroscopic drift remains negligible over the few seconds of typical exercises.

5.3.1.2. Peak and Trough Detection for Periodic Motion

To detect the rhythmic movements of walking or cycling, the pitch signal is processed using a finite state machine (FSM) that alternates between three states: IDLE, INCREASING and DECREASING. These stages reflect whether the pitch signal is steady, rising, or falling. The function responsible for tracking these patterns, called detectCyclesAndSteps, uses these stages to decide what kind of motion is happening. For instance, when the pitch stops rising and starts to fall while in the INCREASING state, the system marks that moment as a "peak" and switches to DECREASING. The opposite marks a "trough." If the device doesn't detect any strong

motion for more than a second, it automatically resets to IDLE to avoid miscounting when not in use.

Each full motion cycle, one peak followed by one trough, counts as a complete movement. On every second peak, the system decides whether the motion was a cycling pedal or a walking step by comparing how strong the pitch movement was. A predefined threshold (4100.0) separates high-intensity movements like pedalling from gentler ones like walking. Depending on the result, the appropriate counter (stepCount or cycleCount) is increased. These counts are then instantly sent over Bluetooth to a central app using a function called updateCombinedData, and they are also saved to memory to make sure the data isn't lost if the power goes off.

To measure cadence, how many steps or cycles happen per minute, the system notes the time of the first movement and uses it to calculate frequency. These results are passed to a function called updateCadenceValues, which keeps track of the last 30 readings and their times. Another function, calculatePeak30MinCadence, then calculates an average using only recent, reliable data from the last 30 minutes, ignoring old or inaccurate readings. This average is saved to memory so that users can track their peak cadence over time, even if the device restarts.

For sit-to-stand exercises, the same pitch data is used in a slightly different way. Two fixed pitch levels are defined to represent sitting and standing. The FSM is expanded to include five states: IDLE, INCREASING, DECREASING, SITTING, and STANDING. It only switches between sitting and standing if the movement is held for at least one second to avoid counting accidental motions. For example, when someone moves from sitting to standing and holds that position, the system logs that as a valid repetition.

Each successful sit-to-stand movement increases the repetition count (repCount); while ignoring the first detected motion in case it's an error. As with walking and cycling, the updated

count is sent to the central app and stored to memory, ensuring the data is both visible and safely saved.

5.3.2. Calibration & Data Smoothing

To ensure accurate measurements, the device begins a short calibration process as soon as it's powered on. During this time, it stays still and calculates a correction value for the built-in gyroscope, which tends to drift slightly even when the device is stationary. This is done by collecting several readings from the gyroscope's Y-axis over a few seconds and averaging them. This average represents the "bias" or natural offset of the sensor. Once calculated, this value is automatically subtracted from all future readings to ensure that a device sitting still reads as zero movement, helping to establish a reliable baseline.

After correcting for this bias, the system smooths out the pitch angle (the device's forward or backward tilt) using a filter that reduces noise and sudden small spikes in the data. This helps to prevent erratic readings caused by quick, minor movements. To further improve accuracy, the device sets a minimum threshold so that tiny twitches or vibrations aren't mistakenly counted as meaningful movements. The smallest change it pays attention to is 0.5 degrees, anything smaller is ignored to avoid miscounting.

Despite these filters, it's still possible for quick back-and-forth movements to be misinterpreted as real actions. To stop this, the device includes a short waiting period, called a debounce timeout, between each valid motion. Once a significant movement is detected, the device waits at least one full second before allowing another one to count. This ensures that rapid reversals (like bouncing or wobbling) don't register as multiple steps or repetitions.

Finally, the system applies one last check to make sure it only reacts to meaningful activity. It looks at how quickly the pitch is changing, using a threshold of 500 degrees per second. Only if a movement exceeds this speed will the device count it as a valid step or cycle. This extra

layer of filtering prevents the device from falsely recording steps during periods of stillness or when experiencing subtle background vibrations.

5.3.3. Data Storage & App Sync

To make sure no data is lost, the Arduino device uses a built-in memory system that saves data directly on the device and also keeps it in sync with the mobile app. When the device is powered on, it runs a startup routine called setup(), which calls a function named loadStoredData(). This function retrieves the most recent counts (like steps, cycles, and peak cadence) from the built-in memory called EEPROM. The FlashStorage library makes this possible, and it ensures that the device can "remember" where it left off before it was turned off.

The information is stored in a simple data structure that includes totals for steps, cycles, and the highest cadence value. These numbers are loaded into working memory (RAM) before the device starts counting again. Each time a step or cycle is recorded, the system updates the live totals and sends them to the mobile app over Bluetooth. It then saves the new values back into memory, but only if they've changed. This prevents unnecessary writing to memory, which helps preserve the device's storage over time.

The BLE connection is also set up during the setup() phase. The mobile app can send commands to the device, for example, telling it to start counting sit-to-stand exercises, by writing messages to a specific Bluetooth characteristic. The wearable reads these commands through a function called processBLECommand(), which extracts any relevant goals and activates the appropriate counting features.

Every time the wearable detects a new step, cycle, or sit-to-stand repetition, it calls updateCombinedData(). This function builds a short message in a format that separates the values with commas (like "stepCount,repCount,cycleCount") and sends it to the app in real time. The app watches for these updates and uses them to refresh its display and store the latest

counts. If the Bluetooth connection ever drops, the app automatically tries to reconnect up to ten times before asking the user to step in.

In addition to Bluetooth syncing, the firmware can also connect to a computer using a USB cable. When a special command called "gather" is sent over this connection, the device responds by printing the saved step, cycle, and repetition totals. This feature provides a backup method for collecting data and ensures that even if the Bluetooth connection is interrupted, the rehabilitation data can still be retrieved safely.

Together, these systems ensure that all intensity data is securely saved on the device and reliably transferred to the mobile app, even in the event of power loss or temporary disconnections.

5.4. Feasibility and Agreement of a Wearable Intensity Tracker for Lower-Limb Stroke Rehabilitation

5.4.1. Introduction

With the development of the DAIM system's intensity tracking component complete, the next critical phase involved evaluating its performance in a real-world setting. This study aimed to assess both the feasibility and agreement of the DAIM wearable tracker in capturing lower-limb rehabilitation intensity, specifically within a TERG and using a chronic stroke population.

The DAIM intensity tracker was designed to capture repetitions and cadence of lower-limb activities such as stepping, cycling, and sit-to-stand exercises. Its target performance threshold was set at ~90% accuracy, a benchmark informed by existing rehabilitation technology research (McAvoy et al., 2022) and feedback gathered from AHPs during in Section 4.3. This benchmark reflects the minimum level of accuracy required for the device to be considered clinically relevant and sufficiently robust for integration into multidisciplinary stroke

rehabilitation pathways. In this study, the DAIM tracker was compared against gold-standard industry reference tools, with a focus on measuring agreement across all key activity types.

5.4.2. Methods

5.4.2.1. Participants

Similarly to Chapter 4, Section 4.4, participants were recruited from the current ongoing trial (clinicaltrials.gov: NCT06787768) at The Sir Jules Thorn Centre for Co-Creation of Rehabilitation Technology, University of Strathclyde (Kerr et al., 2024; Kerr et al., 2023).

5.4.2.2. Testing

Testing involved participants performing structured lower-limb rehabilitation activities at two key points (Weeks 1 and 8) of their rehabilitation programme. Participants wore the DAIM intensity tracker securely attached to their hemiplegic thigh using a Velcro strap, allowing the device to capture step counts, cycling repetitions, squat movements and cadence data.

At Week 1, participants underwent a 20-meter walk test (20MWT) within a motion capture gait laboratory which also operated as the TERG. This test was conducted with participants walking at their preferred pace up and down a set of cones places 10 meters apart with accompanying VICON NEXUS Version 2.15 (VICON, 2024) compatible markers. Step count and cadence were recorded by the DAIM device and simultaneously tracked using a gold-standard VICON NEXUS Version 2.15 motion capture system (VICON, 2024). Reflective markers were placed on participants' ankles and trunk (Figure 36 & Figure 37), and positional data was subsequently processed in MATLAB Version R2023b (The MathWorks Inc, 2024), to determine the reference values for step count and cadence. A general trend toward improved gait was also assessed, hypothesising that increased step stride would correspond to a decreased step count over time.

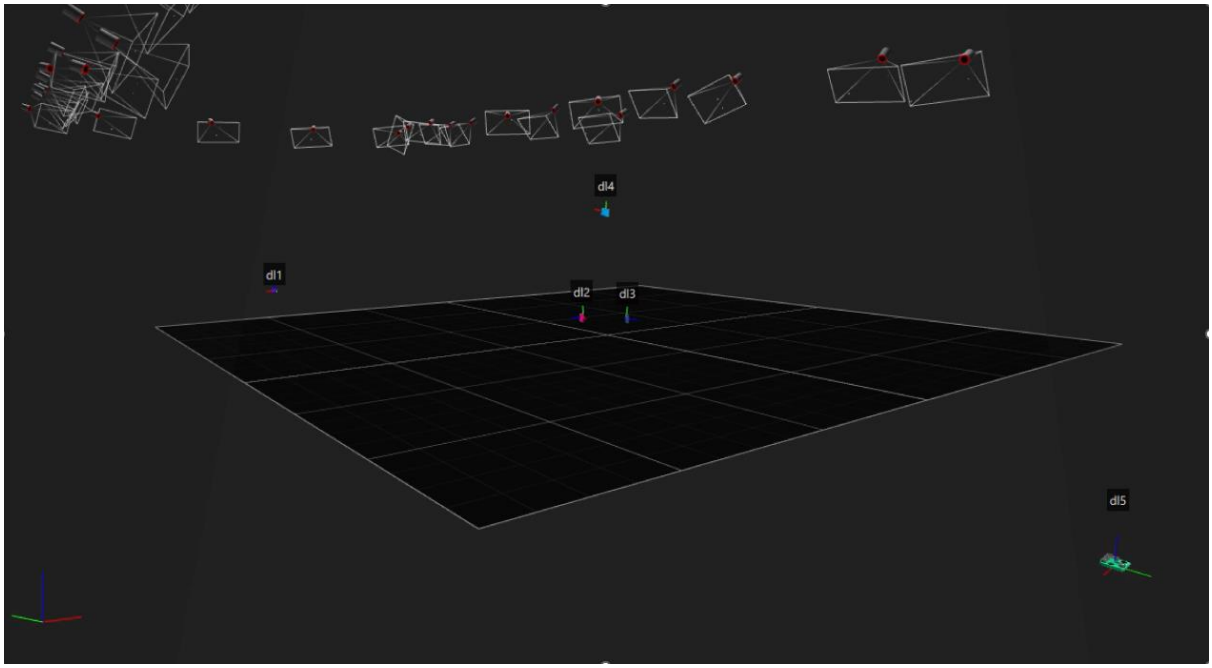


Figure 36 Screenshot of VICON NEXUS Version 2.15 (VICON, 2024) capture of the 20m walk-test showing participant markers and cone markers.

Additionally, during Week 1, participants undertook a 5-minute walking session on the C-Mill treadmill. While VICON NEXUS Version 2.15 tracking was unavailable due to VICON NEXUS Version 2.15spatial constraints, sessions were recorded using a smartphone camera. Step counts and cadence from the DAIM tracker were validated against video analysis and built-in data from the MOTEK treadmill's force plates, which independently captured steps and cadence.

Figure 37 MOTOmed (Medimotion, UK) Intensity Tracking Set-up – DAIM intensity tracker on thigh and VICON Nexus Version 2.15 markers on trunk and ankles for motion capture during cycling.

At Week 8, participants performed a second 20MWT under identical VICON NEXUS Version 2.15 tracking conditions to assess longitudinal improvements in gait metrics. They also engaged in a 5-minute cycling session on a MOTOmed Loop.p.la exercise bike (Medimotion, UK), with DAIM capturing cycle repetitions and cadence. To validate DAIM's performance, cycling data was compared against the Polar Cadence sensor, considered a gold-standard cycling measurement tool, attached directly to the MOTOmed.

Finally, to further test the DAIM tracker's feasibility in typical research scenarios, two participants wore the device for one week when attending TERG sessions (Week 7), capturing step counts, cycling repetitions, and sit-to-stand movements. Data from the DAIM tracker were stored locally and extracted for analysis via Arduino Serial Monitor.

5.4.2.3. Ethics

This study received ethical approval from the Strathclyde University Ethics Committee under the protocol number UEC20/08: Kerr: Generic Framework Application: User experience of a

technology-based rehabilitation programme, Appendix 13. All participants provided informed consent prior to their involvement in the study.

5.4.2.4. Data Management – Intensity measurements

Included in the Arduino's firmware was the ability to measure a user's peak 30-minute cadence over the long-term wear. Peak 30-minute cadence refers to the average number of steps taken per minute during the 30 most active (but not necessarily consecutive) minutes of a day. This metric captures an individual's highest intensity of ambulatory activity, providing insight into their capacity for sustained physical exertion (Tudor-Locke et al., 2019). Unlike total daily step count, which measures overall activity volume, peak 30-minute cadence focuses on the intensity aspect of physical activity.

In stroke populations, measuring peak 30-minute cadence can provide a larger picture of a person's ability to perform higher-intensity bouts of activity. Research suggests that higher peak cadences are also associated with better physical function and reduced cardiovascular risk factors in stroke survivors (Miller et al., 2022).

The DAIM's Arduino firmware maintains a rolling window of the highest cadences recorded over the last 30 minutes by using two fixed-length arrays (stepCadenceValues and cycleCadenceValues, each of size 30) together with corresponding timestamp arrays (cadenceTimes). Whenever a new instantaneous cadence value is computed (inside updateCadenceValues()), the code finds the current minimum entry in that 30-slot buffer and replaces it if the new value is higher, thus ensuring the buffer always holds the top 30 cadences seen.

Once the buffer is updated, calculatePeak30MinCadence() computes the average of only those entries whose timestamps are within the last 30 minutes. This two-step approach confirms that the reported peak 30-minute cadence reflects the true sustained high rates of movement,

smoothing out short bursts and adapting as older data naturally ages out of the time window. To extract this data the “gather” command is sent over the USB link. The printed results are then converted into CSV format with the rest of the printed data (Section 5.3.3).

All raw data extracted from the DAIM intensity tracker was securely uploaded to a password-protected Microsoft OneDrive folder (Microsoft Office, 2024). Access to this folder was restricted solely to the principal investigator and supervising academic and stored for up to five years.

Video recordings from the 5-minute treadmill walk, captured via smartphone, were carefully framed to exclude any identifiable participant features. These anonymised recordings were also stored in the same secure OneDrive location (Microsoft Office, 2024).

All Polar data were extracted from their respective device into a Microsoft Excel 2016 (Microsoft Office, 2024) file and then removed from the device, this file is stored in the same OneDrive location.

VICON NEXUS Version 2.15 motion capture data were collected using pseudonymised participant identification numbers and stored on the VICON NEXUS Version 2.15 system’s secure local server, housed within the locked gait laboratory. MATLAB (The MathWorks Inc, 2024)-processed outputs derived from the VICON NEXUS Version 2.15 data were similarly stored within this restricted-access environment.

5.4.2.5. Analysis

All data collected from the DAIM intensity tracker were exported as CSV files via the Arduino Serial Monitor and subsequently analysed using Microsoft Excel 2016 (Microsoft Office, 2024). Step counts, cycling repetitions, and cadence data were extracted and compared to reference values obtained from industry-standard systems: VICON NEXUS Version 2.15

motion capture, C-Mill MOTEK treadmill data, and the Polar cadence sensor, depending on the activity.

Accuracy was calculated as a percentage using the formula:

$$Accuracy\ (\%) = \left(\frac{DAIM}{Reference}\right) \times 100$$

To assess how closely the DAIM tracker's measurements aligned with established reference systems, several statistical methods were used to evaluate accuracy and agreement across different rehabilitation activities. These included measures for both walking and cycling data, such as step volume, step cadence, cycling repetitions, and cycling cadence.

The Mean Absolute Error (MAE) was calculated to show, on average, how much the DAIM tracker's measurements differed from the reference system, regardless of whether the DAIM over or underestimated the result. This method provides a straightforward measure of average error in the same units as the measurement being analysed:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}|$$

The Root Mean Square Error (RMSE) also quantifies average error but gives more weight to larger errors. It does this by squaring each individual error, taking the average of these squared values, and then applying a square root. This means that any larger differences between the DAIM and reference measurements will have a stronger impact on the result:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}|}$$

To understand how well the DAIM tracker's data follows the pattern of the reference system, the Pearson's Correlation Coefficient (r) was used. This value ranges from -1 to 1, with values

closer to 1 indicating a strong positive relationship. A strong correlation suggests that the DAIM reliably reflects the true activity value, even if there are some consistent offsets:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

From the correlation coefficient, the Coefficient of Determination (R^2) was also calculated. This value shows how much of the variation in the reference data can be explained by the DAIM tracker's data. For example, an R^2 of 0.95 would suggest that 95% of the changes in step count measured by the reference system can be predicted from the DAIM's data, demonstrating a strong level of agreement:

$$R^2 = r^2$$

To determine whether the DAIM measurements were statistically different from those of the reference systems, paired sample t-tests were used. This test compares two sets of values taken from the same individuals under two conditions, the DAIM versus the reference method. A p-value less than 0.05 from this test would indicate a statistically significant difference, indicating that the DAIM produces too large of a difference between the true value.

Finally, Cohen's d was calculated to measure the effect size between the DAIM and the reference system. This gives context to statistical findings by indicating whether the observed differences were small, moderate, or large in practical terms. A value of 0.2 is considered small, 0.5 medium, and 0.8 or above is considered large.

All of these calculations were performed using Microsoft Excel 2016 (Microsoft Office, 2024), specifically with the help of the Microsoft Analysis ToolPak, a Microsoft Excel 2016 add-in that simplifies statistical computations. VICON NEXUS Version 2.15 data was extracted to a csv file and analysed using MATLAB Version R2023b (The MathWorks Inc, 2024).

5.4.3. Results

A total of 13 participants completed the intensity tracking validation study (Table 21) which encompassed all participants who were currently attending the TERG. Participants were predominantly male (77%), with an average age of 67.1 years. Most participants used walking sticks (69%) and approximately half required an ankle-foot orthosis (54%). Six participants (46%) had aphasia, and overall cognitive function was high (MoCA mean = 25.9 ± 4.0).

Table 21 Participant characteristics intensity trial.

Characteristics	**All Participants (n=13)**
Age (years), mean (SD)	67.1 (3.30)
Gender (male/female)	10/3
Hemiplegic side (left/right)	7/6
Time since stroke (months), mean (SD)	45.8 (78.0)
Ankle Foot Orthosis (Yes/No)	7/6
Walking Stick (Yes/No)	9/4
Aphasia (Yes/No)	6/7
Cognition (MoCA), (SD)	25.9 (4.0)

5.4.3.1. 20MWT

The DAIM intensity tracker demonstrated high agreement with the VICON NEXUS Version 2.15 system in tracking step volume. During Week 1, the mean accuracy was 96.0% (±4.6%; Table 22), and in Week 8, accuracy remained high at 95.6% (±3.0%; Table 23). Step cadence accuracy was lower but still acceptable at 89.7% (±5.5%; Table 24) in Week 1, improving slightly to 92.5% (±6.6%; Table 25) by Week 8 due to alterations in the firmware's sensitivity.

Statistical comparisons of step volume (Table 26) showed excellent correlations (Week 1 r=0.982; Week 8 r=0.981), negligible effect sizes (Cohen's D = 0.055), and non-significant differences (Week 1 p= 0.327; Week 8 p=0.337), indicating strong agreement between the

DAIM tracker and the VICON NEXUS Version 2.15 system. Similarly, step cadence comparisons (Table 27) demonstrated strong correlations and minimal error, reinforcing DAIM's accuracy in real-world conditions.

Table 22 Step count accuracy of the DAIM intensity tracker compared to VICON NEXUS Version 2.15 system during the Week 1 overground 20-metre walk test (20MWT).

WEEK 1 STEP VOLUME			
Participant No.	**VICON NEXUS VERSION 2.15 Step Count**	**DAIM Step Count**	**Accuracy (%)**
1	38	43	86.8
2	28	29	96.4
3	22	25	88.0
4	39	37	94.9
5	25	25	100.0
6	51	52	98.0
7	52	50	96.2
8	39	39	100.0
9	35	36	97.1
10	36	36	100.0
11	44	44	100.0
12	21	22	95.2
13	29	28	96.6
MEAN ± SD			**96.0 ± 4.6**

Table 23 Step count accuracy of the DAIM intensity tracker compared to VICON NEXUS Version 2.15 system during the Week 8 overground 20-metre walk test (20MWT).

WEEK 8 STEP VOLUME			
Participant No.	**VICON NEXUS VERSION 2.15 Step Count**	**DAIM Step Count**	**Accuracy (%)**
1	27	28	96.3
2	23	21	91.3
3	19	19	100.0
4	38	40	94.7
5	17	17	100.0
6	42	40	95.2
7	38	35	92.1
8	37	36	97.3
9	27	25	92.6
10	28	26	92.9
11	36	38	94.4
12	18	18	100.0
13	28	29	96.4
MEAN ± SD			**95.6 ± 3.0**

Table 24 Step cadence accuracy of the DAIM intensity tracker compared to VICON NEXUS Version 2.15 system during the Week 1 overground 20-metre walk test (20MWT).

WEEK 1 STEP CADENCE			
Participant No.	**VICON NEXUS VERSION 2.15 Step Cadence**	**DAIM Step Cadence**	**Accuracy (%)**
1	22.6	26.9	81.2
2	52.8	49.3	93.3

3	42.3	50.1	81.6
4	41.9	37.2	88.7
5	44.6	42.6	95.4
6	33.6	36.4	91.6
7	39.4	36.3	92.1
8	40.1	41.1	97.4
9	28.2	32.9	83.2
10	18.8	17.4	92.6
11	48.9	41.7	85.3
12	52.5	55.0	95.2
13	39.7	35.2	88.6
MEAN ± SD			**89.7 ± 5.5**

Table 25 Step cadence accuracy of the DAIM intensity tracker compared to VICON NEXUS Version 2.15 system during the Week 8 overground 20-metre walk test (20MWT).

WEEK 8 STEP CADENCE			
Participant No.	**VICON NEXUS VERSION 2.15 Step Cadence**	**DAIM Step Cadence**	**Accuracy (%)**
1	31.3	37.9	78.8
2	56.8	52.9	93.1
3	51.8	51.2	98.8
4	52.9	50.1	94.7
5	46.4	41.7	89.9
6	35.3	28.4	80.4
7	35.0	33.4	95.4
8	41.5	38.5	92.8

9	32.6	32.2	98.9
10	19.1	20.4	93.1
11	41.7	37.5	89.9
12	51.4	50.0	97.2
13	28.0	28.0	99.9
MEAN ± SD			**92.5 ± 6.6**

Table 26 Comparison of DAIM and VICON NEXUS Version 2.15 step volume tracking across Week 1 and Week 8 during overground walking

STEP VOLUME		
Metric	**Week 1**	**Week 8**
Pearson's Correlation Coefficient (r)	0.982	0.981
R-squared Value (R^2)	0.965	0.962
MAE	1.308	1.385
RMSE	1.901	1.664
Cohen's D	0.055	0.055
p-value	0.327	0.337

Table 27 Comparison of DAIM and VICON NEXUS Version 2.15 step cadence tracking across Week 1 and Week 8 during overground walking.

STEP CADENCE		
Metric	**Week 1**	**Week 8**
Pearson's Correlation Coefficient (r)	0.908	0.956
R-squared Value (R^2)	0.824	0.914
MAE	3.820	2.880
RMSE	4.291	3.618
Cohen's D	0.025	0.155
p-value	0.837	0.100

5.4.3.2. 5-min Treadmill

The DAIM intensity tracker maintained a high accuracy for step volume during treadmill walking sessions, averaging 96.35% (±4.55%; Table 28). Step cadence accuracy was lower, averaging 89.44% (±11.12%; Table 29), suggesting minor difficulties in precise cadence detection on the treadmill, aligning with the results of the 20MWT. Figure 38 shows the DAIM intensity tracker when undergoing the 5-minute treadmill test.

Table 28 Comparison of step volume recorded by the DAIM intensity tracker and C-Mill (Motek Medical, Netherlands) treadmill during the 5-minute walking session.

TREADMILL VOLUME			
Participant No.	**Motek Volume**	**DAIM Volume**	**Accuracy (%)**
1	284	246	86.62
2	226	227	99.56
3	173	179	96.53
5	128	124	96.88
6	209	201	96.17
7	233	230	98.71
10	399	399	100.00
MEAN ± SD			**96.35 ± 4.55**

Table 29 Comparison of step cadence recorded by the DAIM intensity tracker and C-Mill (Motek Medical, Netherlands) treadmill during the 5-minute walking session.

TREADMILL CADENCE			
Participant No.	**Motek Cadence**	**DAIM Cadence**	**Accuracy (%)**
1	58	45.9	79.14
2	61	55	90.16
3	45.7	45.1	98.69

5	39.4	39.9	98.73
6	42.6	42.1	98.83
7	43.65	30.6	70.10
10	54.3	59.5	90.42
MEAN ± SD			**89.44 ± 11.12**

Figure 38(A) DAIM device positioned on the thigh showing step rate and count in real-time. (B) Close-up of the DAIM display showing 61 steps recorded. (C) Close-up of the DAIM display showing 62 steps recorded, demonstrating incremental step count.

5.4.3.3. 5-min Cycle

The DAIM showed excellent accuracy for cycle repetitions during the MOTOmed cycling sessions, with a mean accuracy of 97.78% (±1.11%; Table 30). Cycle cadence accuracy was slightly lower at 94.00% (±7.07%; Table 31), yet still demonstrated strong agreement with

VICON NEXUS Version 2.15 data, confirmed by high correlation values and non-significant statistical differences (Table 32). This result supports DAIM's capability to reliably measure cycling activity intensity.

Table 30 Comparison of cycle volume recorded by the DAIM intensity tracker and VICON NEXUS Version 2.15 motion tracking during the 5-minute cycling session.

CYCLE REPS			
Participant No.	**VICON NEXUS VERSION 2.15 Cycle Cadence (rpm) (reps per minute)**	**DAIM Cycle Cadence (rpm) (reps per minute)**	**Accuracy (%)**
1	194	201	96.39
2	265	271	97.74
5	318	310	97.48
6	65	65	100.00
8	379	374	98.68
10	99	102	96.97
11	169	165	97.63
12	304	312	97.37
MEAN ± SD			**97.78 ± 1.11**

Table 31 Comparison of cycle cadence recorded by the DAIM intensity tracker, Polar cadence sensor and VICON NEXUS Version 2.15 motion tracking during the 5-minute cycling session.

CYCLE CADENCE				
Participant No.	**VICON NEXUS VERSION 2.15 Cycle Cadence (rpm) (reps per minute)**	**DAIM Cycle Cadence (rpm) (reps per minute)**	**Polar Cadence**	**Accuracy of DAIM to VICON NEXUS VERSION 2.15 (%)**
1	31.3	37.9	57	97.89
2	56.8	52.9	70	77.14

5	51.8	51.2	72	97.22
6	52.9	50.1	54	97.96
8	46.4	41.7	70	94.00
10	35.3	28.4	22	98.64
11	35.0	33.4	30	95.67
12	41.5	38.5	64	93.44
MEAN ± SD				**94.00 ± 7.07**

Table 32 Agreement between DAIM intensity tracker and VICON NEXUS Version 2.15 motion capture for cycling repetition count and cadence during MOTOmed sessions.

Metric	Cycle Reps	Cycle Cadence
Pearson's Correlation Coefficient (r)	0.999	0.974
R-squared Value (R^2)	0.997	0.948
MAE	5.125	3.400
RMSE	5.734	4.697
Cohen's D	-0.008	0.052
p-value	0.695	0.592

Table 33 summarises the task-level error rates achieved using the DAIM tracker's thigh-mounted gyroscope sensor across all evaluated rehabilitation activities.

5.4.3.4. Summary

Table 33 Summary of DAIM intensity tracker error rates

Activity	Metric	Sensor	Reference system	Mean accuracy (%)	MAE	RMSE
Overground walking (20MWT, Week 1)	Step volume	Thigh-mounted gyroscope (IMU, Arduino	VICON NEXUS v2.15	96.0 ± 4.6	1.31 steps	1.90 steps

		Nano 33 IoT)				
Overground walking (20MWT, Week 8)	Step volume	Thigh-mounted gyroscope (IMU, Arduino Nano 33 IoT)	VICON NEXUS v2.15	95.6 ± 3.0	1.39 steps	1.66 steps
Overground walking (20MWT, Week 1)	Step cadence	Thigh-mounted gyroscope (IMU, Arduino Nano 33 IoT)	VICON NEXUS v2.15	89.7 ± 5.5	3.82 steps/min	4.29 steps/min
Overground walking (20MWT, Week 8)	Step cadence	Thigh-mounted gyroscope (IMU, Arduino Nano 33 IoT)	VICON NEXUS v2.15	92.5 ± 6.6	2.88 steps/min	3.62 steps/min
Treadmill walking (5-min)	Step volume	Thigh-mounted gyroscope (IMU, Arduino Nano 33 IoT)	C-Mill treadmill force-plates (Motek)	96.35 ± 4.55	–	–
Treadmill walking (5-min)	Step cadence	Thigh-mounted gyroscope (IMU, Arduino Nano 33 IoT)	C-Mill treadmill force-plates (Motek)	89.44 ± 11.12	–	–
Cycling (5-min)	Cycle repetitions	Thigh-mounted gyroscope (IMU, Arduino Nano 33 IoT)	VICON NEXUS v2.15	97.78 ± 1.11	5.13 reps	5.73 reps
Cycling (5-min)	Cycle cadence	Thigh-mounted gyroscope (IMU, Arduino	VICON NEXUS v2.15	94.00 ± 7.07	3.40 rpm	4.70 rpm

		Nano 33 IoT)				
Cycling (5-min)	Cycle cadence	Wheel-mounted magnetic sensor	Polar cadence sensor	–	–	–

5.4.3.5. 1-week trial

Over the course of a one-week trial, two participants with chronic stroke (participants 5 and 12) independently used the DAIM intensity tracker during rehabilitation sessions to informally assess its feasibility during unsupervised rehabilitation activities in the home and TERG setting. The device was worn on the hemiplegic thigh and used to track both general movement volume and peak 30-second intensity during walking and cycling exercises and also track sit-to-stand movements (STS assessments or squats). These two participants were selected for the one-week trial as they had attended rehabilitation sessions most frequently and reliably by Week 7 and had expressed enthusiasm to take part in optional additional feedback activities. One participant did not have aphasia and did not require a walking aid or foot orthosis, while the other also did not have aphasia but did require the use of a foot orthosis.

Participant 5 completed three fully logged sessions, consistently demonstrating higher activity levels (Table 34). Whilst the participant did wear the device correctly without supervision, they did feel like the DAIM did not capture all their squat movements when using the leg-press machine and therefore felt that the sensitivity of the movement pattern algorithm should be increased.

Table 34 Summary of Participant 5s DAIM-Recorded Volume and peak 30-minute cadence during the One-Week User Trial.

Session no.	DAIM volume	DAIM peak 30-minute	Cycle volume	Cycle cadence peak 30-minute
1	363	31.76	764	65.34
2	1046	36.38	379	30.72

3	116	37.73	692	57.47

Participant 2 completed three sessions with recorded data (Table 35). Whilst successful during two sessions, during the second attempt of wearing the device, an equipment issue occurred when a wire became caught and fell out, preventing data storage, and the participant reported the battery falling from the band.

Table 35 Summary of Participant 2's DAIM-Recorded Volume and peak 30-minute cadence during the One-Week User Trial.

Session no.	DAIM step volume	DAIM peak 30-minute step cadence	DAIM cycle volume	DAIM peak 30-minute cycle cadence
1	311	23.08	368	33.18
2	-	-	-	-
3	388	25.55	370	131.17

Across both participants, the DAIM tracker demonstrated good feasibility and alignment with external cadence measures. While minor usability issues were identified (e.g., catching on clothing, loose battery), participants reported minimal discomfort and increasing independence in setup, suggesting strong potential for unsupervised use in research.

5.4.4. Discussion

This study assessed the feasibility and agreement of the DAIM wearable intensity tracker within a real-world rehabilitation context involving chronic stroke survivors. The DAIM tracker demonstrated strong performance, consistently achieving the pre-set accuracy benchmark of approximately 90%, aligning with industry standards and prior rehabilitation technology literature (McAvoy et al., 2022). The DAIM tracker exhibited excellent accuracy in measuring step volume, both in controlled overground walking conditions (96.0% at Week

1, 95.6% at Week 8) and during treadmill walking (96.4%). These findings, reinforced by negligible statistical differences and correlation metrics, indicate that the DAIM system effectively captured accurate step volumes compared to the gold-standard VICON NEXUS Version 2.15 and MOTEK systems. While step cadence accuracy during overground walking was slightly below the set benchmark initially (89.7% at Week 1), the improvement observed by Week 8 (92.5%) highlights the DAIM tracker's capability to reliably measure and adapt to varied gait patterns among stroke survivors.

The 20MWT provided the most comprehensive assessment of gait across all participants, including those with aphasia and/or requiring assistive devices. Lower accuracy results observed, particularly for Participant One, were associated with pronounced shuffling gait patterns. Shuffling gait, characterised by short, dragging steps, reduced foot clearance, and difficulty initiating movement, significantly impacts mobility, independence, and quality of life by increasing fall risk (Celik et al., 2025; Mirelman et al., 2019; Pistacchi et al., 2017). These gait irregularities present notable challenges for wearable sensors, such as accelerometers and IMUs, due to their difficulty in detecting subtle, asymmetrical movements, especially under real-world conditions influenced by environmental factors and individual variability. Additionally, sensor placement and calibration are critical; improper positioning can compromise data accuracy. Recent literature suggests optimal sensor placement at the hip or bilateral thighs for accurate gait measurement post-stroke, contrasting with commonly marketed wrist-worn devices (Sun et al., 2025). Moreover, the absence of standardised protocols for gait analysis with wearables in stroke rehabilitation further contributes to variability in data interpretation (Rech et al., 2025). It was theorised that the DAIM trackers' utilisation of solely gyroscope data benefited from a greater sensitivity to rotational movements, making it particularly effective in capturing the angular velocity changes associated with gait phases. This approach was therefore advantageous over accelerometer-

based methods, which primarily measure linear acceleration and might miss subtle angular changes characteristic of shuffling gait patterns.

The DAIM tracker maintained acceptable accuracy levels, with a minimum of 86.8% for step volume and 78.8% for step cadence, even in participants with severe shuffling gait. An upward trend in accuracy from week 1 to week 8 corresponded with participants' gait improvements due to consistent rehabilitation, reinforcing the device's utility in tracking general progress. In cases with less severe or absent shuffling, the DAIM consistently surpassed the predefined benchmark (~90%). Reflecting the stakeholder feedback from Chapter 3 that absolute accuracy was considered less critical than providing users with reliable evidence of their engagement and progression in rehabilitation.

It is important to note that, aside from the informal one-week trial, the researcher consistently placed the device onto participants rather than allowing self-placement. This decision was intentional, as the primary focus of this study was to evaluate sensor accuracy and validate the firmware rather than assess the physical usability or aesthetics. Ensuring firmware accuracy was critical because failure to meet accuracy benchmarks would necessitate a comprehensive redesign, whereas physical and ergonomic features could be addressed iteratively. Consequently, the study concluded with the informal one-week trial, after successful validation of sensor accuracy. This final phase enabled rapid collection of preliminary feedback on device usability and ergonomics, providing valuable insights for future development and refinement of the wearable.

Cycling repetition tracking was effective, yielding an accuracy of approximately 97.8% but cycling cadence accuracy presented slight variability (94.0%), possibly due to minor inconsistencies in sensor positioning or motion irregularities in the users gait patterns. Only 8 participants completed the 5-minute cycling test, this is due to some participants being unable

to use the device due to their size or some users not feeling comfortable in using the MOTOmed. Nevertheless, the strong correlation and statistical agreement indicate the DAIM tracker's reliability for measuring cycling-based rehabilitation tasks. It should also be noted that a higher degree of accuracy was expected as the user is using powered cycling devices and therefore these will produce much more stable movement patterns compared to hemiplegic gait patterns. Future studies should therefore consider measuring the devices accuracy when cycling on a non-stationary bike in real-world conditions (e.g. road or trail).

When contrasting the DAIM tracker's performance against the Polar cadence sensor, the results suggest that DAIM provides a closer approximation to the VICON NEXUS Version 2.155 system, which served as the reference standard. In several cases, the Polar sensor, which is mounted on the wheel of the exercise bike rather than on the user's limb, reported significantly inflated cadence values, for example in Participant One (57 rpm vs. DAIM's 37.9 and VICON NEXUS Version 2.15's 31.3) and Participant Three (72 rpm vs. DAIM's 51.2 and VICON NEXUS Version 2.15's 51.8). This overestimation may result from the Polar's position on the bike wheel, which captures rotations regardless of user exertion or movement quality. In contrast, the DAIM tracker, worn on the thigh, measures the user's actual limb motion and consistently yielded cadence values more closely aligned with the VICON NEXUS Version 2.15 system. This suggests DAIM's superiority in capturing true user-generated intensity. Additionally, the polar cadence sensor may rely on GPS tracking to accurately measure cadence and as this was stationary cycling the GPS function was not applicable. With the DAIM components currently costing £70 when purchasing off the shelf, the DAIM device can offer a more cost-effective solution for more accurate rehabilitation monitoring compared to the Polar cadence sensor (£64.50) and other commercial alternatives, with potential for even lower costs through scaled manufacturing.

User's Peak 30-Minite Cadence showed the large variability of measured efforts throughout sessions, with step cadence ranging from 23.08-25.55 steps/min with participant 5 and 31.76-37.73 steps/min for Participant 2. Participant 5's cycling peak jumped dramatically from 33.18 to 131.17 rpm between Sessions 1 and 3. This likely reflects differences in the types of activities completed or engagement levels on that day, but it may also point to inconsistencies in movement pacing. It was also found that the step and cycle volumes do not always correlate directly with peak cadences. For example, Participant One2 logged the highest step volume (1046) in Session 2, but peak cadence was not the highest, suggesting the participant exercised longer but not necessarily at their most intense. This highlights the importance of measuring both duration and intensity, as a high rehabilitation "dose" (volume) does not always equate to a high exertion level.

The Peak 30-Minute Cadence metric offers clinicians and researchers a valuable tool for assessing the intensity of physical activity during rehabilitation. By capturing the highest cadence sustained over a 30-minute window, it provides a reliable indicator of peak exertion, allowing for meaningful comparisons across sessions or individuals. This measure can be used to evaluate whether a user is meeting established intensity thresholds. Additionally, trends in Peak 30-Minute Cadence over time can help predict functional outcomes, such as walking endurance or independence in daily activities. AHPs can use this information to tailor rehabilitation plans by setting progressive cadence targets that encourage incremental improvement, while also monitoring for consistency of effort. For instance, a drop in peak cadence might indicate fatigue, decreased motivation, or a need for programme adjustment. In research settings, the metric can help classify participants efforts by intensity level, evaluate the efficacy of interventions, and support personalised rehabilitation strategies that align with individual progress and recovery goals.

During the extended one-week trial, participants provided valuable insights regarding device usability in daily rehabilitation sessions. Informal feedback revealed a good user acceptance and ease of use however highlighted key minor practical challenges that could be improved upon with the next iteration of the device for the final acceptability study (Chapter 7), such as occasional interference from clothing and a single instance of wire disconnection.

One limitation of this study was the absence of blinding or randomisation when comparing the DAIM intensity tracker to the reference systems. The same investigator who managed data collection also placed the devices and conducted the assessments, introducing the potential for observer bias. Additionally, participants were aware they were being observed and compared against standard systems, which may have influenced their behaviour or exertion levels. While this approach was appropriate for a feasibility and agreement study focused on technical validation, future studies aiming for clinical implementation would benefit from incorporating blinding and randomisation to reduce bias and enhance the robustness of findings.

5.4.5. Design Refinements

Based on user feedback from the 1-week trial, two key design issues with the wearable intensity tracker were identified and addressed in the next prototype iteration. The first concern was that the battery, previously housed externally, had fallen off during use. Originally, the battery was intended to be temporarily placed in the user's pocket due to its size; however, this proved problematic when users wore garments with shallow pockets, as the battery could easily slip out. Additionally, some users wore clothing without any pockets, such as sports leggings, raising concerns about consistent and secure placement. The second issue involved wires becoming disconnected, often due to exposure and accidental snagging. To resolve both problems, the wearable's band was redesigned. The updated version (Figure 39) replaced the original exposed configuration (Figure 35) with a more secure and user-friendly design. This

included the integration of a fabric pocket to hold the rechargeable battery in place, ensuring it remained secure regardless of clothing type. Additionally, the wiring was fully enclosed within a fabric casing, preventing wires from catching on clothing or equipment. These modifications were made to enhance comfort, reliability, and durability, especially in dynamic rehabilitation settings involving individuals with mobility or dexterity impairments.

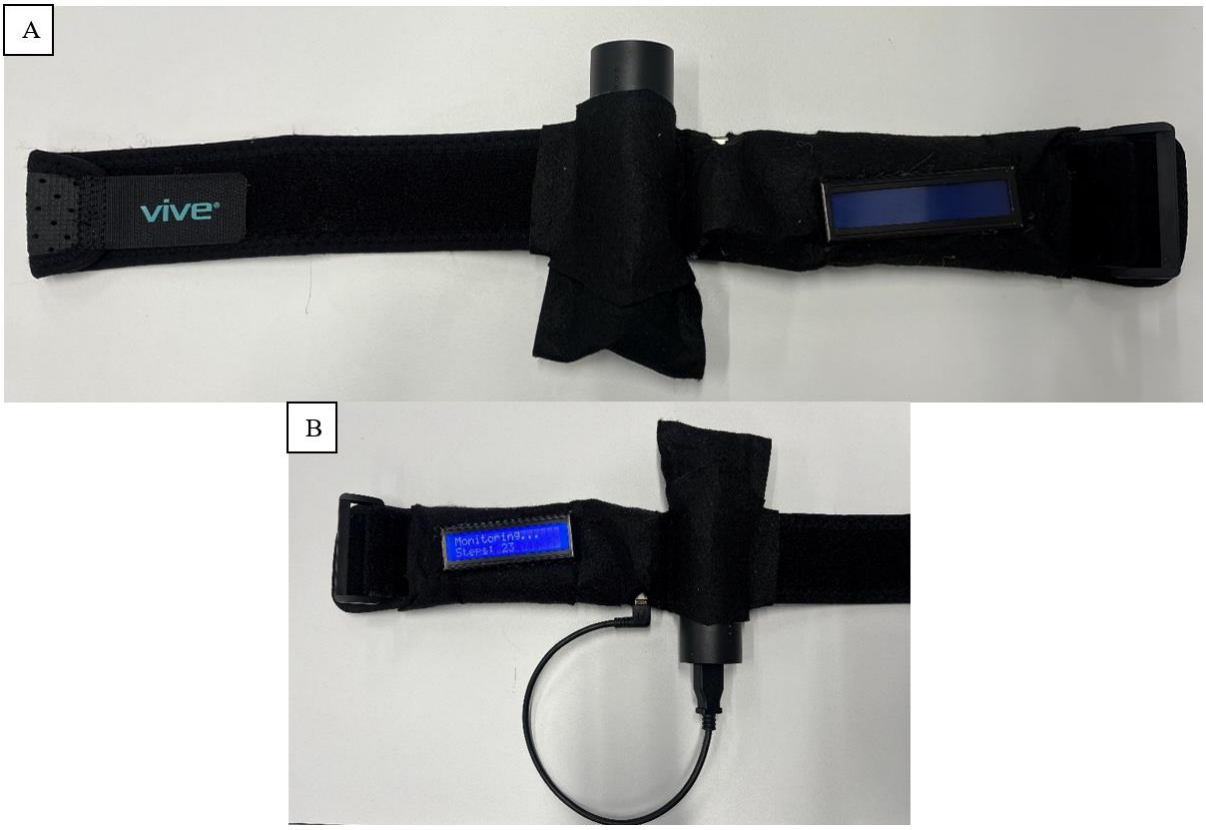


Figure 39 (A) The updated removable thigh tracker that attaches with a Velcro strap. (B) The tracker turned on using a short cable plugged into a rechargeable battery, with an LCD screen showing your step and cycle rep counts.

5.5. Chapter Summary

This chapter detailed the full design, development, and evaluation of the wearable intensity tracking component of the DAIM system. Created in response to a recognised need for more standardised, accurate, and accessible methods for tracking rehabilitation intensity, the wearable tracker was shaped by stakeholder-driven design inputs identified in Chapter 3. The

final prototype was built using an Arduino-based gyroscope sensor, chosen for its cost-effectiveness, precision, and compatibility with the system's lightweight, user-friendly goals.

The DAIM wearable tracker was developed to automate the measurement of rehabilitation intensity capturing step count, cadence, and repetition volume offering a practical alternative to manual reporting, which often suffers from inaccuracy, incompleteness, and inconsistency. Its real-world application was evaluated through feasibility testing in a research rehabilitation setting, with results demonstrating strong agreement with industry gold-standard systems such as VICON NEXUS Version 2.15 motion capture and C-Mill (Motek Medical, Netherlands) treadmill measurements. Additionally, the device outperformed consumer-grade options like the Polar cadence sensor in capturing user-specific movement data, largely due to its strategic sensor placement on the hemiplegic thigh rather than relying on external hardware-mounted methods.

While the device showed high accuracy, especially in step and repetition counts, it also revealed challenges associated with tracking more complex gait patterns, such as shuffling commonly seen in stroke populations. Notably, the DAIM's performance improved over time in line with participants' rehabilitation progress, reinforcing its potential to track functional gains over extended periods. The integration of peak 30-minute cadence metrics further demonstrated the system's ability to provide AHPs and researchers with nuanced data for assessing exertion consistency, tailoring progression targets, and predicting functional outcomes, whilst also highlighting the importance of differentiating between duration and intensity, as a high rehabilitation "dose" does not always equate to a high exertion level.

In response to feedback from the study, the wearable underwent a design refinement that addressed practical concerns such as battery displacement and wire exposure. These co-design updates enhanced the device's comfort and reliability in dynamic rehabilitation environments.

In conclusion, the results affirm that the DAIM intensity tracker meets the essential criteria for accurately and reliably monitoring rehabilitation intensity. Next stages now involve developing the mobile application which will integrate both the dosage and intensity data into one user friendly platform that incorporates the final community and tracking design requirements set out before final acceptability testing.

Chapter 6. Mobile Application System Design and Development

6.1. Introduction

Following the selection and refinement of the final concept (Section 3.4.3.1) and the validation of the dosage and intensity tracking systems (Chapter 4 & Chapter 5), the next stage was to integrate these data streams into a cohesive mobile application. The primary goal was to provide an accessible, user-friendly interface for tracking rehabilitation dose and intensity, adhering closely to the user-defined requirements gathered during the co-design process (Section 3.4.3.1). Key priorities identified by users included gamification of rehabilitation goals to enhance motivation, clear and intuitive self-rehabilitation indicators to guide rehabilitation activities, and community features to foster peer support and social engagement. This chapter details the iterative design and development process undertaken to meet these requirements, leading up to the comprehensive testing phase discussed in the final acceptability study (Chapter 7).

6.2. System Architecture

6.2.1. Android Studio

For the final acceptability study (Chapter 7), it was important to ensure that participants could effectively use smartphones provided by the research team, while enabling rapid prototyping and iterative testing capabilities. Android devices were selected for this purpose due to their dominant global market share (~88% in 2016), making them widely accessible and cost-effective for broader dissemination (Boyd et al., 2017). Development was conducted using Android Studio, the official Integrated Development Environment (IDE) for Android

applications, which supports Kotlin and Java programming languages, further providing flexibility for app design.

Android Studio streamlines the development process by offering code editing, debugging, built-in emulators, and an instant build-and-deploy feature, allowing rapid testing and iteration of the user interface (UI) and functionality. Its emulator capability is particularly valuable for testing app compatibility across various and tablet models and so can simplify extensive testing scenarios for the application (Bhargava et al., 2024). Additionally, Android's robust support for BLE enables seamless, real-time integration with custom hardware components through standard BLE APIs which deem it highly applicable for the integration of the intensity trackers real-time feedback (Wang et al., 2022). Compared to Apple's iOS, Android's open architecture and robust community support offer greater development flexibility and ease of rapid prototyping, which can allow the app to go through an iterative design methodology, aligning with the core design methods of this project (Woodbridge et al., 2009). Additionally, Android Studio's status as a free development tool further supported its suitability for the project's prototyping requirements.

6.2.2. Overview

The DAIM app serves as the central interface for users to interact with their rehabilitation data, with its data storage abilities the app can also act as a method for users to relay their exact rehab data back to their appropriate AHP. The app communicates with the DAIM system's components using BLE, Wi-Fi and PhPmyadmin protocols. A high-level system architecture showing the major components and the flow of data between them is found in **Error! Reference source not found.** with an expanded version in Appendix 7. An Entity-Relationship diagram is provided (Figure 41) to show how the data is organised and connected in the

database. All application code was developed in Android Studio using the Kotlin language, and the complete source listing is provided in Appendix 6.

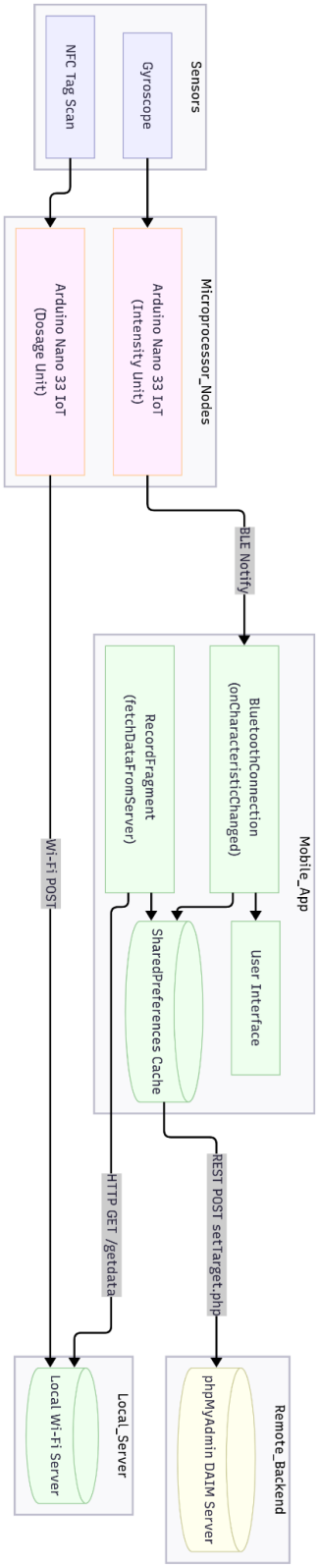


Figure 40 High-level data-flow architecture of the DAIM system, illustrating the dosage and intensity trackers, one capturing live movement via BLE, the other logging session events via NFC and feeding said live data into the mobile app's data handlers and synchronised both to a local Wi-Fi server and to a remote phpMyAdmin.

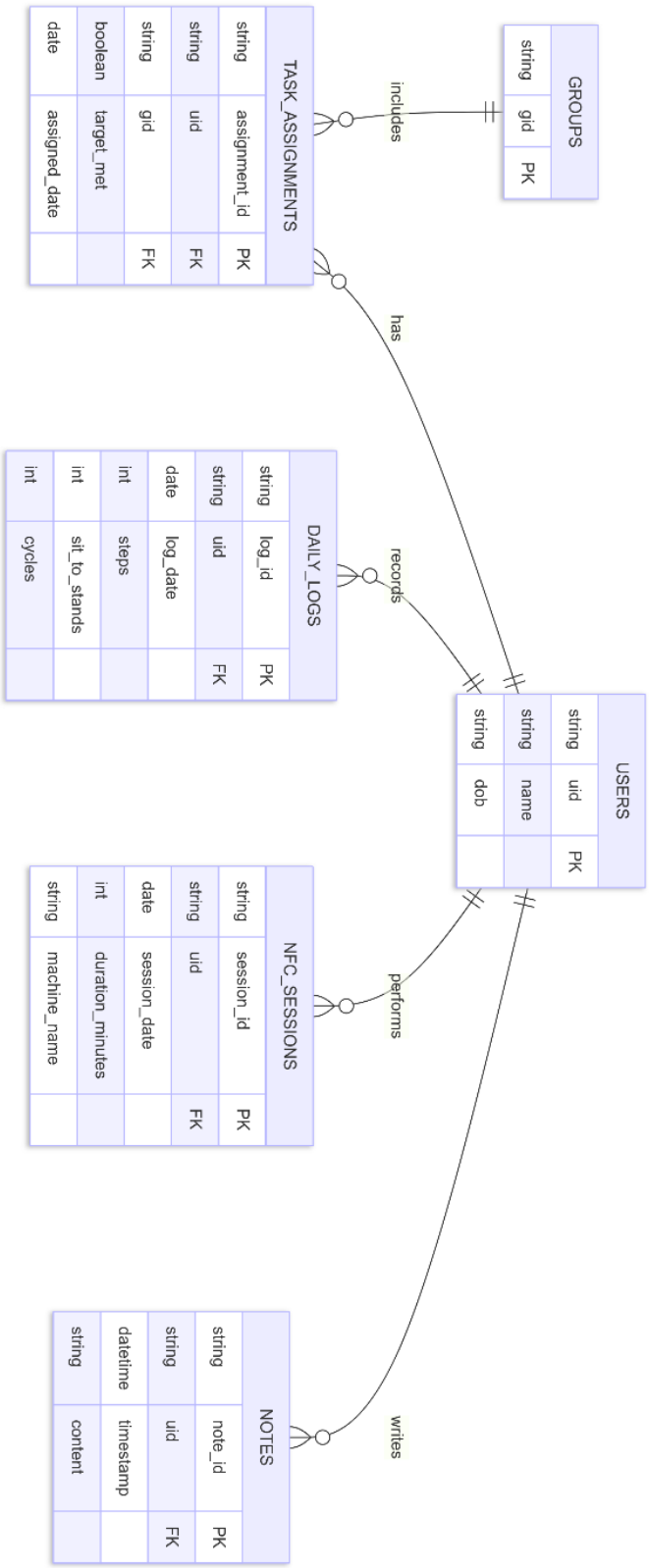


Figure 41 An Entity-Relationship diagram for the DAIM application, depicting primary keys (PK), foreign keys (FK), and the one-to-many relationships between users, their task assignments, daily intensity logs, NFC-logged sessions, and rehabilitative notes.

6.2.3. BLE

The DAIM app manages communication with the wearable intensity tracker using BLE, a wireless technology frequently employed for sensor devices due to its low power usage and widespread compatibility. At the heart of this communication is the BluetoothConnection script, responsible for creating a stable connection between the mobile app and the wearable Arduino device by using its unique device address.

Once a connection is established, the wearable device begins transmitting each pre-defined intensity metric: the number of walking steps and steps/min, sit-to-stand repetitions, and cycling revolutions and cadence. To streamline this process, the device sends these distinct measurements as a single, comma-separated string (for example, "1050, 22, 12" would indicate 1050 steps, 22 sit-to-stand movements, and 12 cycling revolutions). Upon receiving this data, the app separates and interprets these individual metrics, storing each type of activity data separately for quick retrieval and future reference.

Recognising that wearable technology often experiences disruptions, such as interference, signal dropouts, or temporary disconnections (particularly common due to user movement, battery optimisation features, or idle device states), the DAIM app has been designed with robustness in mind. When the connection to the wearable device is unexpectedly lost, the app automatically attempts to reconnect, up to ten times. If reconnection remains unsuccessful, the app proactively alerts users, prompting them with clear messages to manually attempt reconnection.

To prevent any loss of valuable exercise data during periods of disconnection, the DAIM app employs local caching through the mobile phone's internal storage. Specifically, it continuously saves the most recent measurement. This caching ensures no data is permanently lost if the BLE connection temporarily fails. Meanwhile, the wearable continues counting activities

independently, storing these updated metrics until reconnection is re-established (5.3 Signal Processing). Once connectivity is restored, the latest activity data seamlessly synchronises with the app, updating historical activity logs to reflect the most accurate and current information.

6.2.4. Wi-Fi

Complementing the live BLE intensity tracking, the DAIM app also incorporates NFC to log rehabilitation activities, particularly in structured settings such as clinics and research environments (Chapter 4). In these controlled environments, a networked sensor platform securely captures and transmits activity data over a private Wi-Fi network, completely independent of internet connectivity. This architecture enhances data protection and security, as sensitive rehabilitation data is contained entirely within a closed network, reducing the risk of external interception, unauthorised access, or dependency on public cloud infrastructure.

On the mobile app side, synchronisation with the local network is managed by the RecordFragment.kt script (Appendix 6), specifically the fetchDataFromServer() method. This method retrieves critical information such as the user's unique ID (UID), specific exercise machines used, and session durations via a local server using a lightweight Representational State Transfer (RESTful API). A RESTful API is a widely used method that enables communication between software applications through standardised internet protocols, typically via simple commands and lightweight data formats such as JSON. After verifying that the retrieved UID matches the user's profile, the app updates any relevant interface elements, such as progress bars and task indicators, to reflect the current rehabilitation status.

The NFC-based dosage tracking subsystem follows a similar robust approach to the BLE subsystem. Data captured from NFC interactions are temporarily stored both on the local Wi-Fi server and the Arduino microprocessor. Once the device reconnects to the local Wi-Fi

network, the app periodically retrieves and caches this data locally, ensuring no loss of crucial session information.

6.2.5. phpMyAdmin

The DAIM app integrates with a remote database system managed via phpMyAdmin to facilitate secure data sharing, user-group management, and progress tracking across multiple users. phpMyAdmin, a web-based interface, provides a convenient and secure way for clinicians and researchers to access and manage data stored remotely in a MySQL database.

To enable communication between the app and this database, a web-based interface composed of PHP scripts (setTarget.php, getTargetsMet.php, and getUUID.php) is hosted on a dedicated university server (https://devweb3000.cis.strath.ac.uk/~aes02112/daim_server/). These scripts collectively form a RESTful API. This remote database interaction occurs securely over HTTP, ensuring ease of communication and accessibility.

Within the DAIM app, communication with the remote database is simplified with Retrofit, a networking library specifically designed for Android applications (Appendix 6). Retrofit manages the technical aspects of sending requests and receiving responses to allow for efficient and reliable data exchange.

When a new user first opens the app, a unique identifier (UUID) is generated using a dedicated function. The app then assigns the user to an available online group by querying group sizes to the online server. The server will check for balanced group participation by assigning users to groups with fewer than five members. Once assigned, the user's information is securely transmitted and stored in the remote database.

Each group is composed of up to five users, based on their unique identifiers (UIDs). As new users create accounts, they are automatically placed into the next available group. Once a group reaches five UIDs, the server begins filling the next group in sequence. This structured

grouping allows for coordinated tracking of group progress and encourages peer accountability. The group-based approach supports the gamified and community-focused elements of the DAIM system by promoting shared progress and collective achievement.

As users complete their daily rehabilitation tasks, their progress is continuously monitored and visually represented through progress bars within the app interface (Section 6.4.5). When all tasks for the day are marked as complete, the app communicates this achievement back to the online server. Group-level progress is periodically assessed by fetching collective user data from the online server. If every group member completes their tasks, the app visually acknowledges this collective success.

Data integration with the remote database requires an active internet connection. Recognising the inherent instability in wireless environments, the DAIM app retains all collected BLE and NFC data locally on the device, enabling seamless data synchronisation once connectivity is re-established. This robust approach ensures continuous data integrity and reliability, safeguarding the accuracy and completeness of users' rehabilitation records.

The phpMyAdmin backend not only securely stores individual and group performance data long-term but could be repurposed in later protype iterations for authorised clinicians and researchers to have direct access to review, evaluate, and export data as needed, this would require that the AHP be given secure login credentials.

6.3. User Interface (UI) Design and Accessibility

The UI design requirements (Section 3.4.3.1) defined from the original co-design focus groups and polls centred on three principles: clarity, motivation and accessibility. First, the app’s display had to give stroke survivors an at-a-glance picture of “what I’ve achieved today” by showing live rep & cycle step counters, clear progress bars and give a clear idea of how the ‘team’ was performing. Second, the UI needed to sustain motivation through subtle

gamification mechanics, such as daily goals, streak indicators and simple trophies, whilst letting users look back at cumulative totals to see their personal efforts. Finally, every screen, button and text field interaction had to remain usable for people with hemiparesis, aphasia or low digital confidence, so the design employed large touch targets, sans-serif fonts, high-contrast colour palettes, phrasing capped at a primary-school reading level and a "turn-on-and-go" workflow that avoids nested menus or multi-step configuration.

Achieving these targets were highly important for the implementation of the device in real-world settings. About half of survivors experience cognitive changes and one third live with aphasia, reducing language comprehension, reading speed and working memory (Stroke Association, 2025). These communication and cognitive changes mean that standard mobile interfaces can become literal barriers to use with literature stressing that applications should push for emphasis on short, plain labels, high contrast icons that can be recognised without reading, picture or animated feedback, and consistent layouts that minimise working memory load (Cha, 2024; World Wide Web Consortium, 2015; Zhu et al., 2024).

6.3.1. Accessibility Standards

WCAG 2.2 to Mobile Applications is an informative World Wide Web Consortium (W3C) Note that explains how every principle, guideline and success criterion in the Web Content Accessibility Guidelines (WCAG) 2.2 can be interpreted when the digital product is a native, hybrid or mobile/web app rather than a desktop web page. Each success criterion is classified by conformance level, in which Level A is the essential baseline that if sites or apps that fail will block access for some users, whereas Level AA builds on that baseline by adding stricter colour contrast, reflow and input method provisions and is the level most organisations aim to meet for legal and policy reasons (World Wide Web Consortium, 2025).

The Mobile Accessibility Task Force (MATF) in 2018 also added and highlighted the key criterion apps should meet for optimal accessibility. It was decided that these key criteria were the standard the DAIM app was to adhere to. WCAG offers a single, globally recognised benchmark for digital accessibility. Because it is cited in UK, EU and US law and backed by detailed technical notes, it covers more situations than platform rules that apply only to Android or iOS and is easier to test than broad management standards such as ISO 9241-171.

Building the app to WCAG therefore can meet user expectations whilst also aligning with commonly used practises in research and industry. Interestingly a scoping literature review of 15 suitable publications involving studies of 12 eHealth services found that 8 did not provide any explanation into their accessibility with only five publications using WCAG guidance (Jonsson et al., 2023). Another systematic review into home assessment mHealth apps for community living found that none of the apps met the accessibility criteria when evaluated against WCAG 2.1 (Shin et al., 2024). A summary of how the DAIM Android application performs against each relevant WCAG 2.2 Level A and AA success criterion is in Appendix 8.

6.3.2. Accessibility Limitations

Although the DAIM app already avoids colour-only cues and supplies tap-based alternatives to every gesture, there are several accessibility gaps that could be improved upon with additional time and resources. There was also a limitation of coding knowledge as the researcher had little knowledge of Android Studio prior to developing the app.

To improve the app for accessibility, custom images that were added to code (e.g., tower floors) without implementing Android Studios' TalkBack feature to allow the app to verbally label the image for those with visual impairments. Additionally, these custom graphics were not tested for 4.5:1 contrast and so users may not be able to clearly see the images if they have low vision or colour-blindness. The reasoning behind not testing these custom images were that the project

was under a strict deadline to deliver the rapid prototype so that final acceptability testing could be undertaken which was a high priority for the project. In addition, as the final study was using phones provided by the university, the researcher was already aware of the screen dimensions and therefore could optimise the UI for those specific dimensions and return to the contrast measuring at a later point.

The code also lacks dynamic-type support as no view is set with sp-based text that scales to the user's font preference; therefore, users cannot currently alter the font size to their specific needs. Finally, the app does not use any kind of audio ques as feedback which does ignore some of the feedback presented in the focus groups in which a third of users would have preferred audio or haptic feedback. There is haptic feedback present but only to signify if the user's phone is correctly connected to their intensity tracker and if the intensity tracker disconnects.

6.4. Core Features and Functionality

All the application code was developed in Android Studio using the Kotlin language, and the complete source listing is provided in Appendix 6.

The DAIM app was designed to host 3 key fragments, a 'Record' tab to log the real-time intensity data and provide the user with a gamified sit-to-stand exercise (held in an 'Exercise' tab), a 'You' fragment with the purpose of displaying the personalised rehabilitation goals of the user with dosage tracking capabilities for when the user is completing said goals, and a 'group' fragment with the purpose of displaying the Groups collective goal, how many member so the group have completed their goals and the visual feedback reward in the form of a tower. Figure 42 and Figure 43 present a high-level overview of the core features of the DAIM application and how the app communicates to each tab within the app.

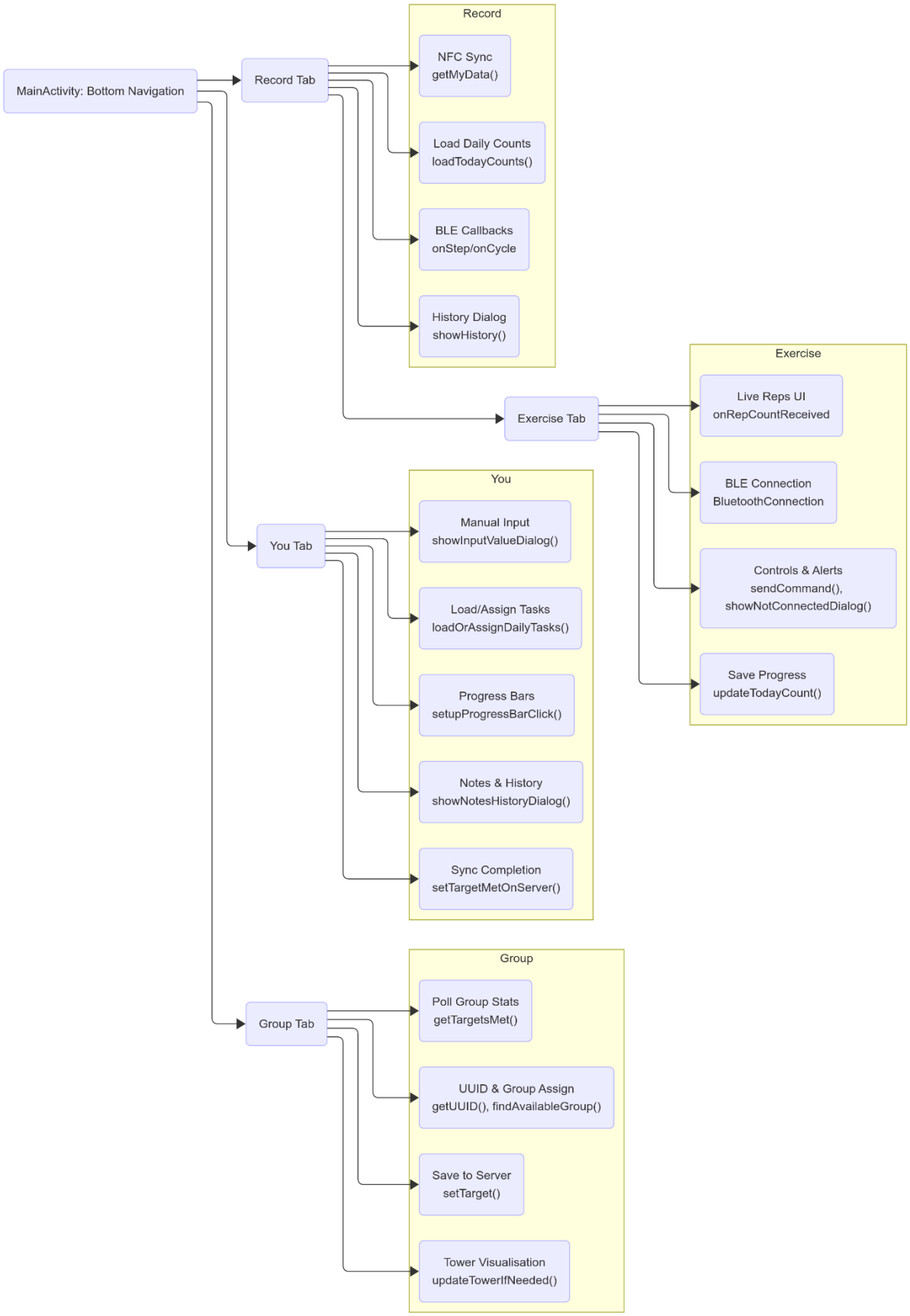


Figure 42 High-level system architecture of the DAIM Android app, illustrating the main navigation entry point (MainActivity) and the core responsibilities of each tab.

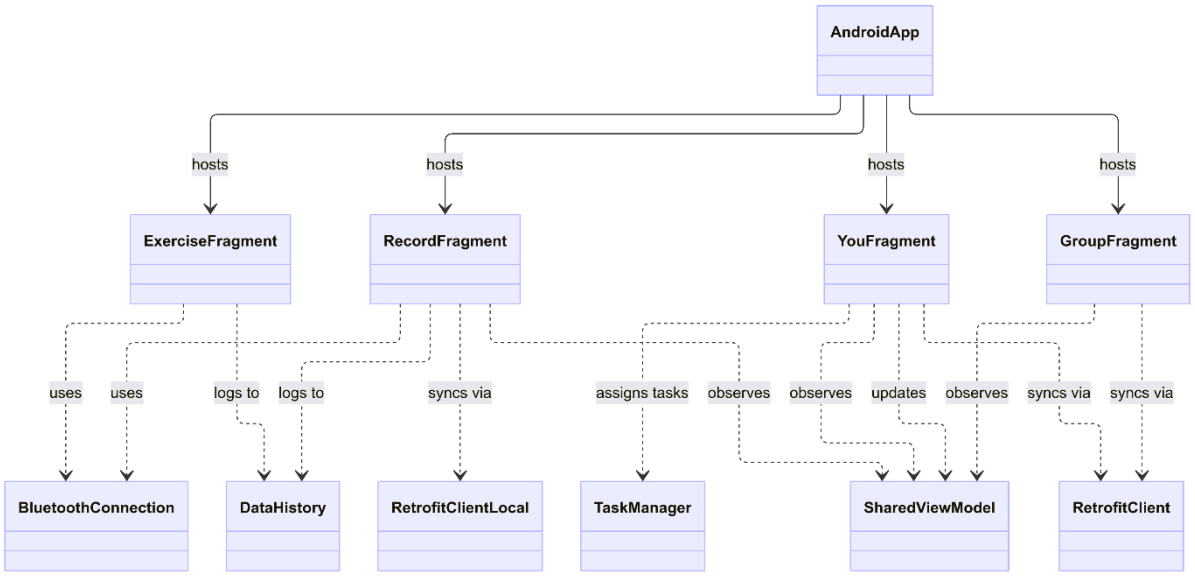


Figure 43 Component diagram of the DAIM app, showing the Android application hosting four fragment components (Exercise, Record, Group, You) and their dependencies on core services.

6.4.1. User Profile Generation

The app guides new users through an intuitive profile-generation process to capture essential personal details and rehabilitation preferences. This user-friendly setup ensures the app's functionality aligns closely with individual needs and rehabilitation goals.

When users launch the DAIM app for the first time, it automatically checks if their user profile is complete. If the app identifies incomplete or missing profile information, it directs users to enter essential details such as their name and date of birth on an initial screen (Figure 44). Once

users confirm these basic details, they proceed to a series of tailored questions designed to personalise their rehabilitation experience.

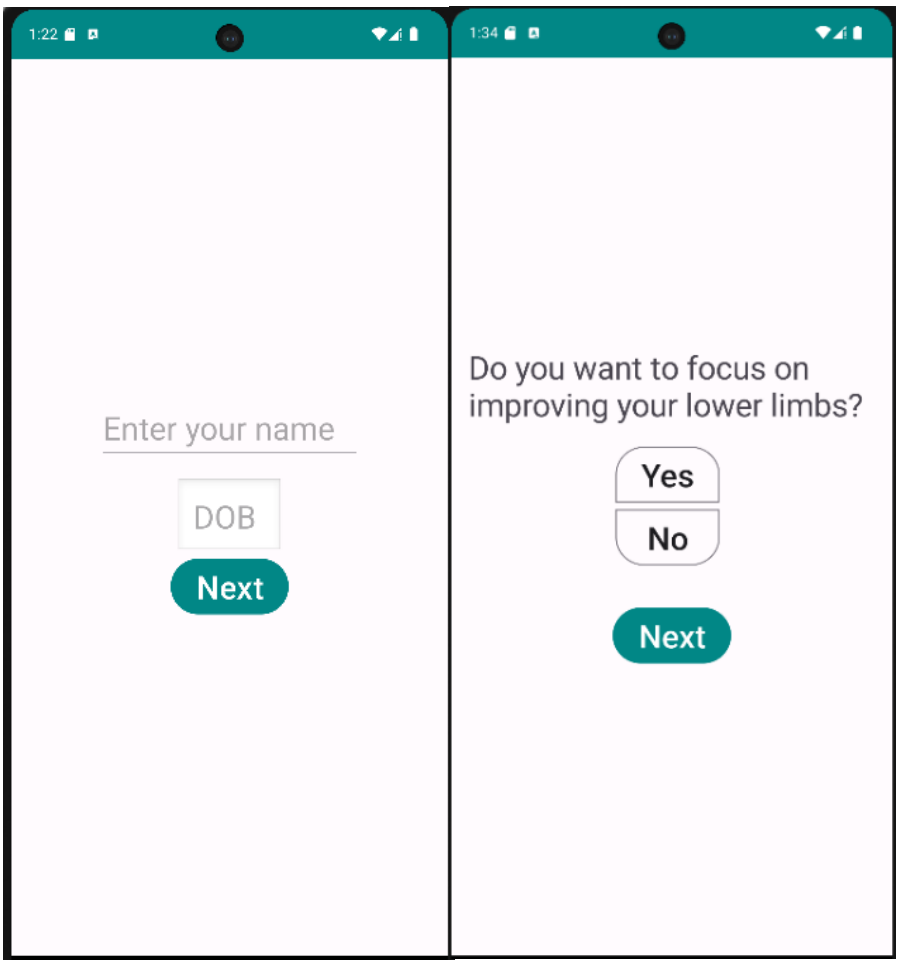


Figure 44 (left) Opening screen for new user, (right) example of profile generation questions.

The app presents six multiple-choice questions that capture key aspects of the user's rehabilitation preferences:

- Do you want to focus on improving your lower limbs?
    - Answers: Yes or No
- Do you want to improve your stamina or strength?
    - Answers: Stamina or Strength
- How often do you want to exercise per week?
    - Answers: 3 days, 5 days or Everyday

- How long can you currently exercise before needing a break?
    - Answers: 10 minutes, 20 minutes or 30 minutes/more
- What type of exercises do you prefer?
    - Answers: Walking, Cycling, Treadmill or Squats
- What is your experience level with exercise and rehab?
    - Answers: Beginner, Intermediate or Experienced

The six profile-setup questions take influence from evidence-based parameters that AHPs use when tailoring post-stroke exercise prescriptions, so collecting them at onboarding lets the app auto-generate tasks that are both safe and motivating.

Asking whether the user wants to focus on lower-limb recovery first distinguishes those whose primary goal is gait from those prioritising upper-body or cognitive or speech, matching current research and guidance which suggests that programmes should target the body region most affected by motor impairment to maximise functional gains (Duncan et al., 1998; Gangwani et al., 2022).

A stamina-versus-strength choice captures the “training goal” dimension of the FITT-VP framework (Frequency, Intensity, Time, Type, Volume, Progression); aerobic endurance work improves walking speed and cardiovascular health, whereas resistance work boosts force production and balance, and both are recommended by stroke guidelines but at different dose parameters (Billinger et al., 2015; Gordon et al., 2004).

Specifying preferred weekly frequency (3, 5 or 7 days) and current continuous exercise tolerance (10-, 20- or 30-minute sessions) lets the algorithm scale total rehabilitation minutes to the individual while still supporting the user to meet the 3 hour rehabilitation guidelines (NICE guideline [NG236], 2023).

Offering a range of modalities: walking, cycling, treadmill or STS also accounts for personal preference, which is a strong predictor of long-term adherence and is particularly important because some stroke survivors dislike or cannot access certain movements (Eng, 2010; Geidl et al., 2018).

Finally, capturing self-rated experience (beginner, intermediate, experienced) allows initial intensity and task complexity to be graded, with novice exercisers benefiting from simpler or shorter tasks, whereas experienced users can be challenged with higher step-cadence or resistance goals, research has also shown that accounting for user experience can help to sustain motivation and engagement over time (Lee et al., 2022). All profile-generation questions also underwent a review and refinement by a qualified physiotherapist, promoting clinical relevance and user-friendliness to enhance the overall effectiveness of the DAIM rehabilitation system.

6.4.2. Daily Goal Setting

The DAIM app generates each day's rehabilitation goals by combining the user-defined preferences to confirm that assigned tasks remain both achievable and appropriately challenging. This daily goal-setting process is triggered every midnight so that users wake up to clearly defined, personalised rehabilitation activities ready to engage them.

The app assesses key elements from each user's profile, specifically whether their rehabilitation is focused primarily on lower-limb improvements, stamina enhancement, and their self-reported exercise experience level. These insights, gathered during the initial profile setup, directly shape the rehabilitation tasks assigned daily. For example, a beginner user who prioritises lower-limb strength and stamina might receive tasks such as short walking goals combined with brief STS sequences and cycling activities designed for stamina building. Conversely, users who report a higher level of exercise experience and a focus on strength may

receive more tasks, such as extended time on resistance equipment or more demanding sit-to-stand sequences.

Once generated, each day's personalised rehabilitation tasks, complete with clear descriptions and specific numerical targets, are saved and initiated as progress bars within the app's You Fragment (Figure 45).

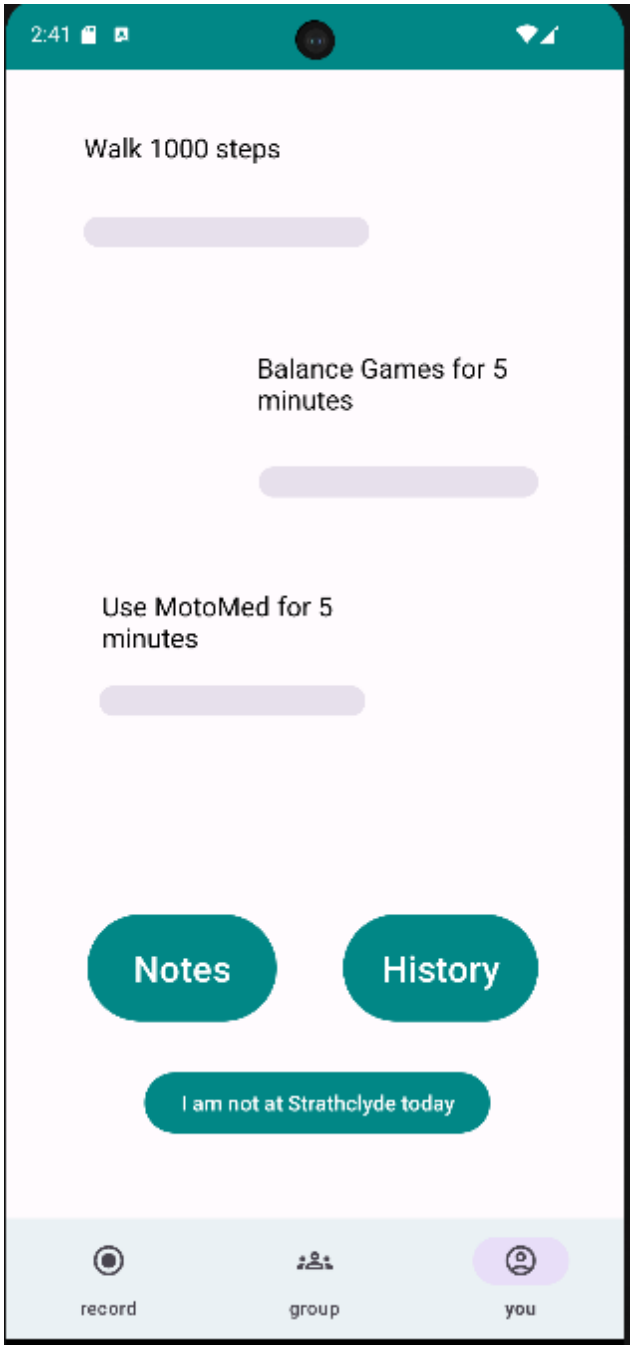


Figure 45 UI showing an example of someone who wanted to focus on stamina however thought of themselves as a 'novice'.

When a task is completed, a trophy icon appears alongside the now-greyed-out task name, giving a clear visual cue of success (Figure 46).

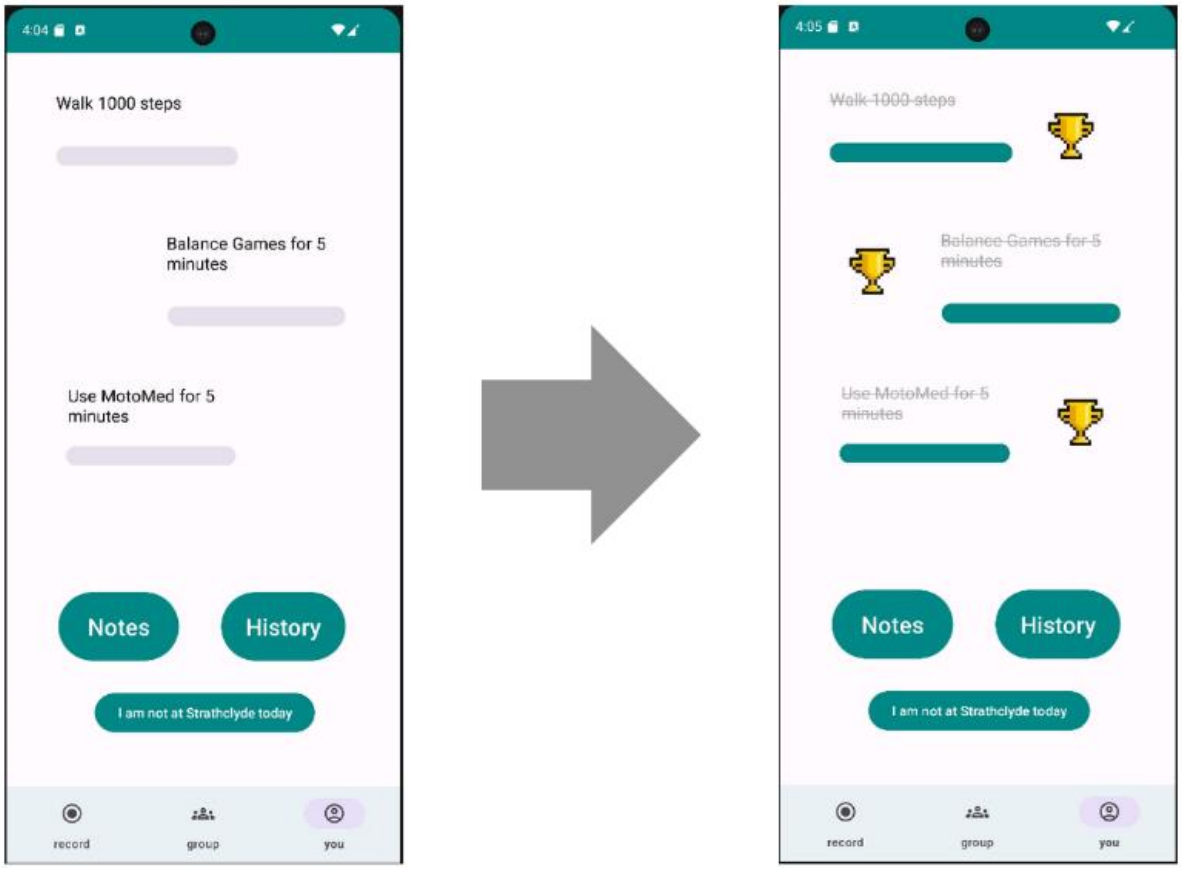


Figure 46 Example of progress bars before and after completion

6.4.3. Gamification of STS

The STS "game" is initiated entirely from the Android app, users select their desired number of repetitions and start the game with a simple tap, triggering communication between the app and the wearable intensity tracker via BLE (Section 6.2.3). If the wearable tracker is disconnected when the user attempts to start, the app promptly alerts the user, offering options to reconnect or pause the activity to ensure that no data or user efforts are lost.

Once connected, as each repetition of the sit-to-stand exercise is completed, the wearable device communicates this progress back to the app. The app responds instantly by updating visual feedback on the user's screen in the form of a pixelated heart that gradually fills as the user approaches their chosen repetition target. When the goal reaches 100% completion, the heart is replaced by a pixelated trophy, giving immediate positive feedback (Figure 47).

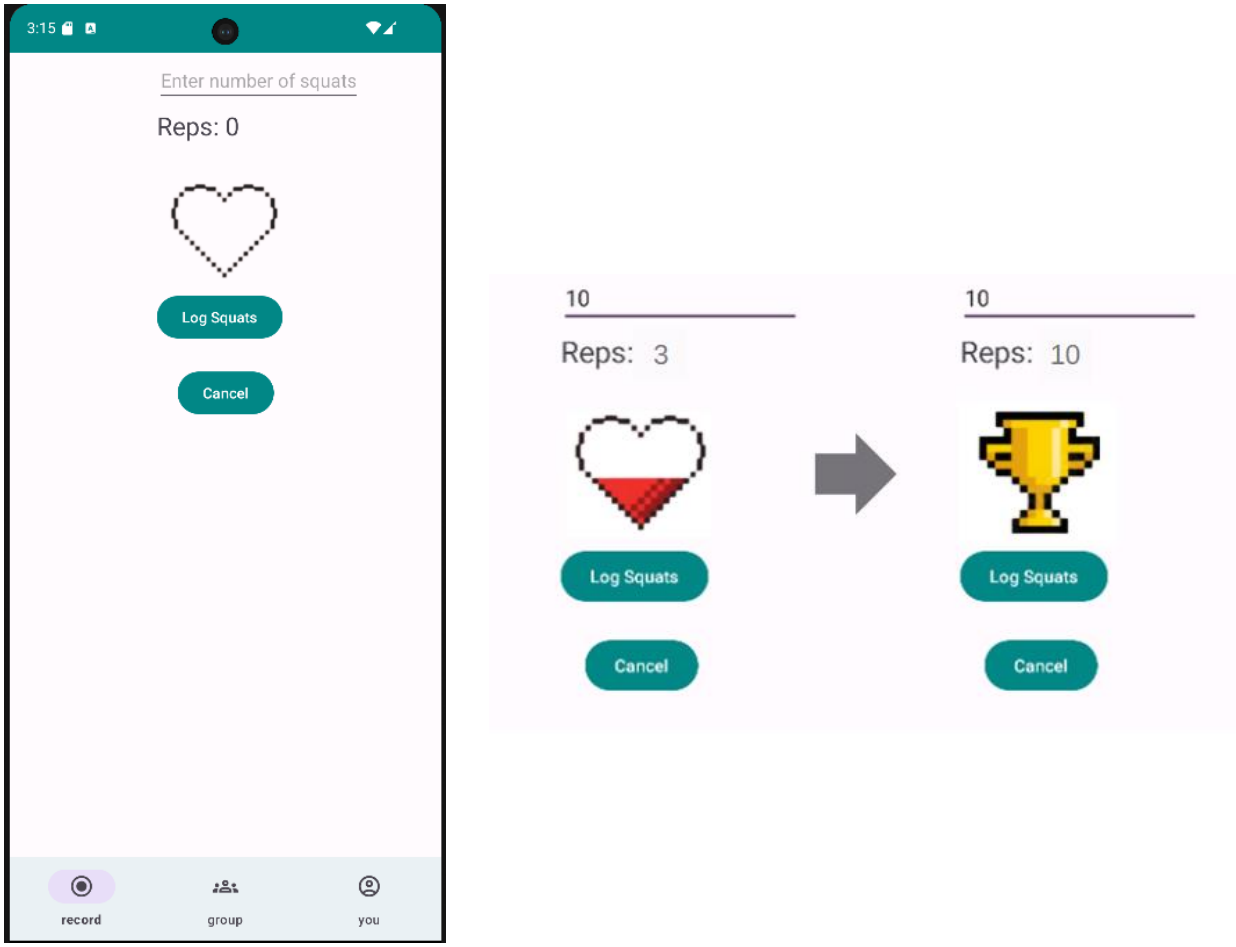


Figure 47 Example of how the STS game works.

This simplified gamification approach was carefully designed based on evidence and stakeholder feedback. Firstly, research supports that stroke survivors consistently rank accurate rep-counting, progress monitoring and immediately understandable visual cues among the most motivating wearable features, ahead of complex graphics or audio alone (Daryabeygi-

Khotbehsara et al., 2024; Tosto-Mancuso et al., 2022). This was also found to be the case during initial focus groups with stakeholders (3.4.2 Results).

Second, framing each STS exercise as a finite “quest” (e.g., 30 sit-to-stands) applies Self-Determination Theory, which is the use of clear goals plus instantaneous feedback to boost intrinsic motivation, which is shown to predict better home-exercise adherence in chronic stroke (Grech et al., 2024; Langerak et al., 2024).

Third, a simplified game can satisfy gamification requirements without adding extra cognitive load or complexity. Finally, the progressive frame sequence offers a delight factor (positive emotion scores improve when games use small, successive rewards rather than distant leaderboards) and avoids text, making it culturally and linguistically transferable (Sakabe et al., 2021).

6.4.4. Gamified Community Tracking Feature ("Team Tower")

The ‘Group Fragment’ includes a unique community-tracking feature known as the "Team Tower," designed to foster group support and collective achievement amongst users. This feature visually represents the group's daily rehabilitation progress through a growing virtual tower.

Each user's daily rehabilitation goals directly contribute to their group's success. When an individual completes all assigned daily tasks, their achievement status is immediately communicated to a remote server (Section 6.2.5). Meanwhile, the app continuously updates the group's collective progress, ensuring that every member can easily track how close their

team is to achieving its daily target. For example, users can clearly see updates such as "Met Target: 3 out of 5," providing a real-time snapshot of group progress (Figure 48).

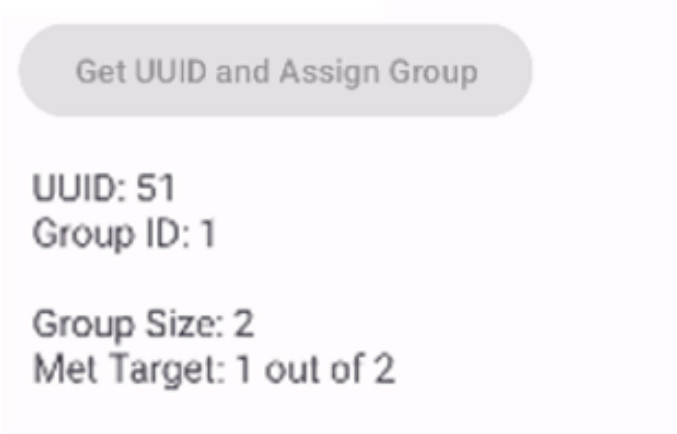


Figure 48 Example of what the user would see in the Group Fragment

The "Team Tower" grows taller only when all members of a group successfully complete their individual daily tasks, providing a sense of collective responsibility. Once the app detects that every group member has met their daily goals, it adds a new floor to the virtual tower, visually celebrating the group's collective success (Figure 49).

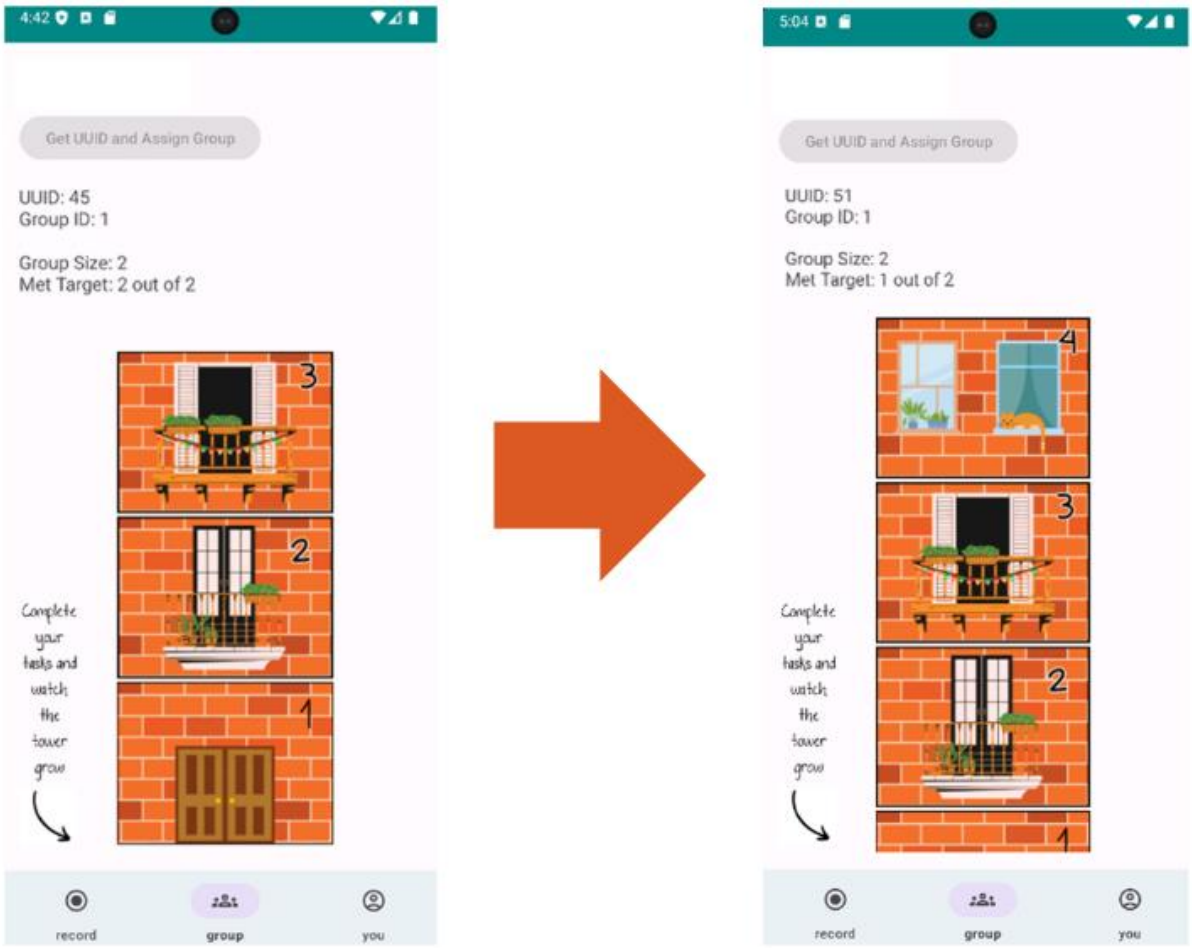


Figure 49 Example of the tower feature in the GroupFragment

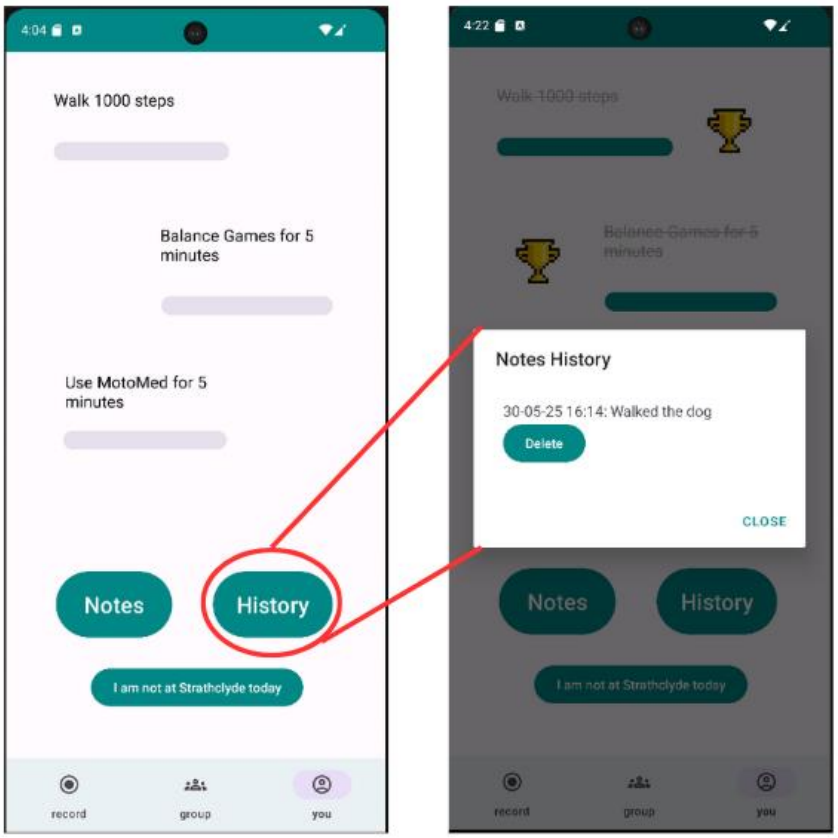
Each successful group day is represented by an additional floor in the tower, creating an ongoing visual representation of sustained teamwork and consistent progress.

6.4.5. Logging and Feedback

The app gives users multiple forms of visual feedback in each fragment (Record, Group, You and Exercise, Figure 43) as they work through their rehabilitation targets. The first being real-time image feedback in the Exercise Fragment as they complete their gamified STS target (Section 6.4.3).

The You section, users can visually track daily progress through filling progress bars and completion icons, which reinforce goal completion (Section 6.4.2). Users can also add personalised notes. This feature acknowledges that rehabilitation extends beyond structured tasks. By tapping the "Note" button, users can record any meaningful activity that they feel

contributes to their recovery (e.g. walking the dog or gardening) (Figure 46). These notes are saved with a timestamp and can later be reviewed or edited through the "History" button. If no



notes exist, a message reminds users: "No notes yet." (Figure 50).

Figure 50 Example of Notes feature in You Fragment

In the Record section, users receive real-time feedback on physical activity levels like walking steps and cycling repetitions. As data arrives from the wearable sensor, it is logged with a timestamp, creating a running history (Section 6.2.3). By tapping the "Show History" button, users can review daily summaries of past activity levels. The app groups records by date and displays the most recent value for each day. Users also have the option to clear this history, with a confirmation message appearing immediately afterwards to indicate success (Figure 51).

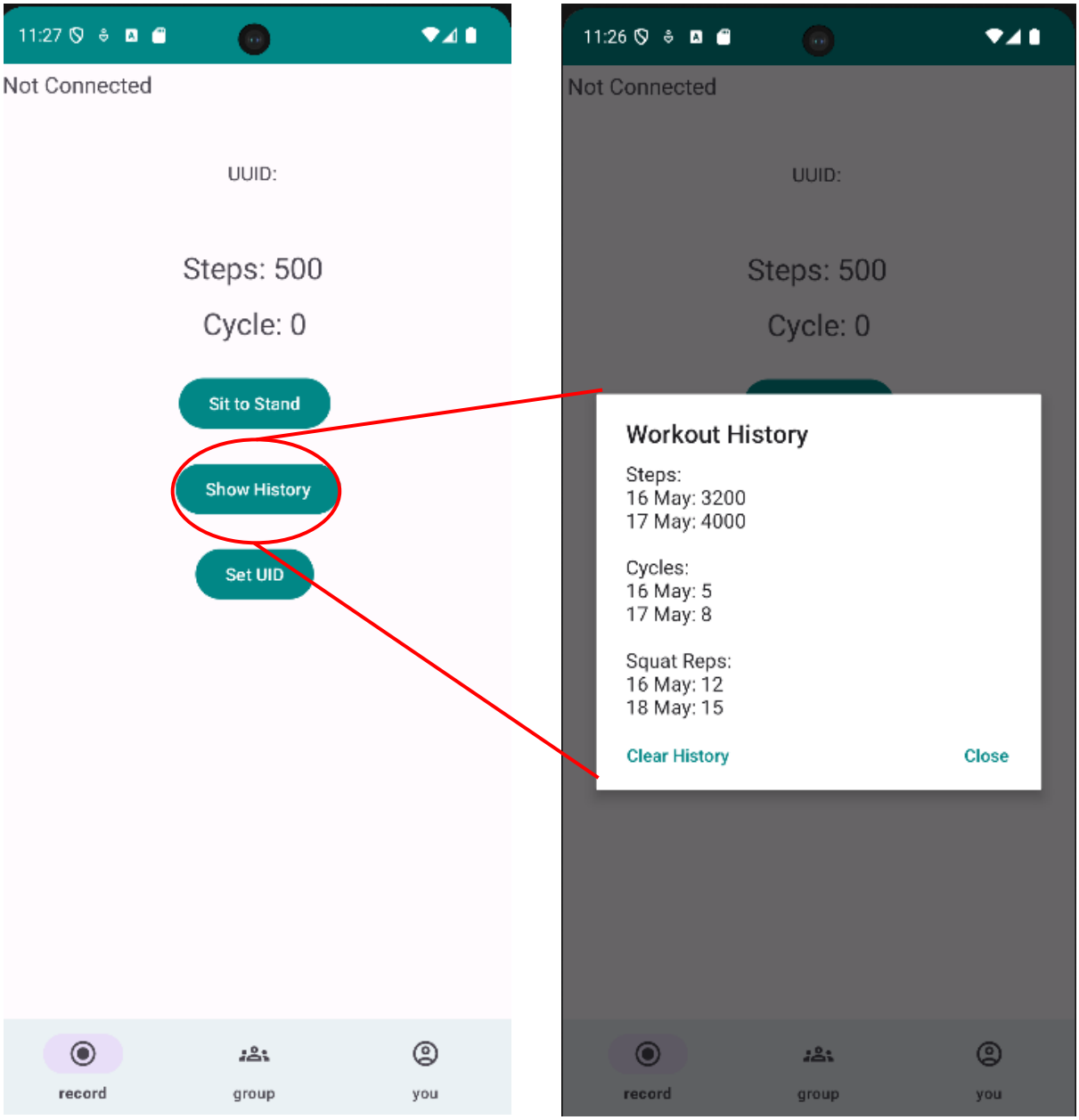


Figure 51 Record tab of app showing history of intensity

Finally, in the Group section, group feedback is visible through the 'Team Tower' feature (Section 6.4.4).

Together, these logging and feedback mechanisms help transform the rehabilitation experience into a transparent, supportive, and personalised process. By empowering users to see their own progress and engage with it meaningfully, the DAIM app strengthens both adherence and

confidence throughout the recovery journey whilst providing users with accurate accounts of their rehabilitation dosage and intensity.

6.5. Chapter Summary

This chapter details the design and development process of a mobile application aimed at integrating rehabilitation dosage and intensity data into a user-friendly format for individuals recovering from stroke. Guided by clearly defined stakeholder-driven requirements established in Chapter 3, the application was developed using Android Studio and Kotlin, selected due to their suitability for rapid prototyping and ease of testing. The system's architecture was chosen to support efficient and secure data handling, employing BLE for real-time data streaming with the wearable intensity tracker, Wi-Fi for dosage data synchronisation, and phpMyAdmin to effectively manage and store user progress data securely and remotely.

Core functionalities of the application included personalised daily goal setting, a gamified sit-to-stand exercise, community-driven tracking ("Team Tower"), additional logging capabilities and immediate visual reward feedback. All functionalities were directly informed by co-design input with all features aimed to enhance motivation, adherence, and engagement by leveraging principles of gamification, peer support, and tailored task allocation.

The user interface was carefully designed to maximise accessibility to those with aphasia and upper limb impairments and therefore ensure ease of use. Initial integration testing demonstrated effective communication between the mobile application, intensity tracker, and dosage tracker, validating the feasibility of providing real-time rehabilitation progress updates.

Initial feedback collected during informal stakeholder demonstrations also indicated a good level of acceptance and enthusiasm towards the application's concept and features, particularly highlighting the motivational value of visual feedback and community integration, thus confirming that the app met the initial design requirements. Nonetheless, it was determined

that a comprehensive acceptability study should also be conducted with the fully integrated DAIM system before introducing further iterations or enhancements to the application.

Chapter 7. Final Acceptability Study of DAIM

With the completion of all prototype components and inclusion of the online community feature and feedback game (Section 6.4.4), a final acceptability study was conducted. The primary aim of this study was to evaluate the extent to which the DAIM system met the original design requirements, and to identify areas for further development, where necessary. This study provided an opportunity to gather in-depth user feedback on the system as a whole, rather than isolated component testing, as explored in Chapters 4 to 6. To ensure participants gained a comprehensive understanding of the system, they were encouraged to use the full DAIM system over the course of one week, both during home-based use and within their lab-based rehabilitation sessions.

In addition to assessing overall system acceptability, secondary outcomes explored participant preferences regarding cooperative versus competitive approaches to achieving daily goals. This analysis aimed to identify the most effective method for supporting motivation and adherence, and to align with the initial design requirements.

7.1. Design

This study followed a mixed-methods, field-based usability evaluation employing a case-series approach to assess whether the co-designed DAIM system meets the initial user-centred design criteria. Utilising both quantitative (surveys) and qualitative (semi-structured interview) methods contribute to capturing both structured views of the system and more nuanced opinions, this is supported by recent rehabilitation technology evaluations explicitly describing themselves as usability studies using similar mixed methods to gather experience-based and holistic feedback (Dittli et al., 2023; Toh et al., 2023).

Østervang et al also gives an example of a convergent parallel mixed-methods design taken from Creswell and Clark (Figure 52) to evaluate the usability of a health information system in a clinical setting (Creswell & Plano Clark, 2018; Ostervang et al., 2024).

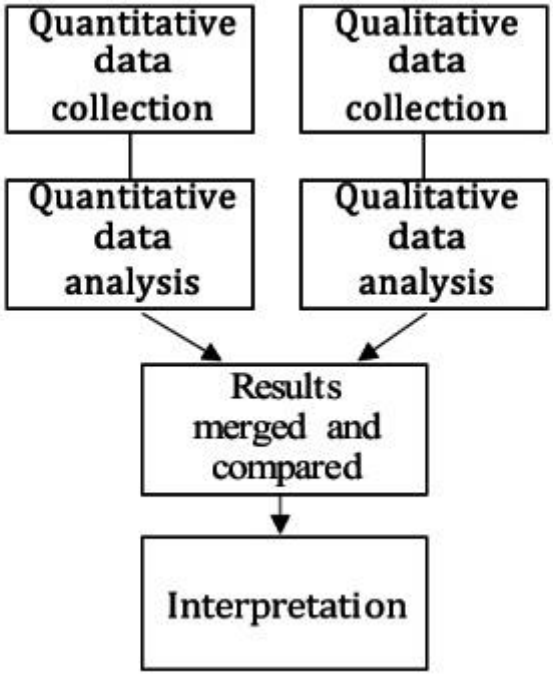


Figure 52 Convergent design flowchart (Creswell & Plano Clark, 2018)

This study also observes/tracks the participants' use of the system in their real-world environments to provide authentic capture of the usage patterns, highlighting real-world usability challenges and verifying whether the system genuinely meets user needs and initial design criteria (Crowe et al., 2011; Tan, 2011).

Small uncontrolled studies in tele-rehabilitation have also been labelled pre-experimental pilot studies when only a few participants were tested without a control group (Almojaibel, 2016). Using a small sample size is also supported by additional literature which argue that early-stage evaluations of novel technologies often start small because of costing and feasibility factors (Bacchetti et al., 2011).

As per the framework of this thesis the purpose of this mixed-methods study is to complete the final evaluation by collecting sufficient data to compare to the original design requirements. The use of a mixed-methods approach is also supported by existing literature, notably the

Centre for eHealth and Wellbeing Research (CeHRes) Roadmap (**Error! Reference source not found.**). This framework emphasises that after the co-design and development phases, a summative evaluation should e undertaken to assess how effectively the implemented solution meets the original design requirements and addresses user needs as set out in Section 3.4.3.1 (Moore et al., 2019; van Gemert-Pijnen et al., 2011). This differs from formative evaluations which are defined as iterative tests that identify and fix problems, whereas a summative evaluation typically measures whether predefined usability criteria and safety requirements are satisfied (Wiklund et al., 2010). Literature also argues that co-creation prioritises the end-user's perspective as well as continuous collaboration between stakeholders throughout the systems development (Elbers et al., 2021).

This study also follows the final principles of the MRCs final stage of the development of complex interventions methodologies: Evaluation – assessing an intervention using the most appropriate method to address the research questions. In adopting a mixed-methods approach, this creates a robust evaluation of intervention outcomes, consistent with the MRC's guidance on complex interventions (Section 3.3.4).

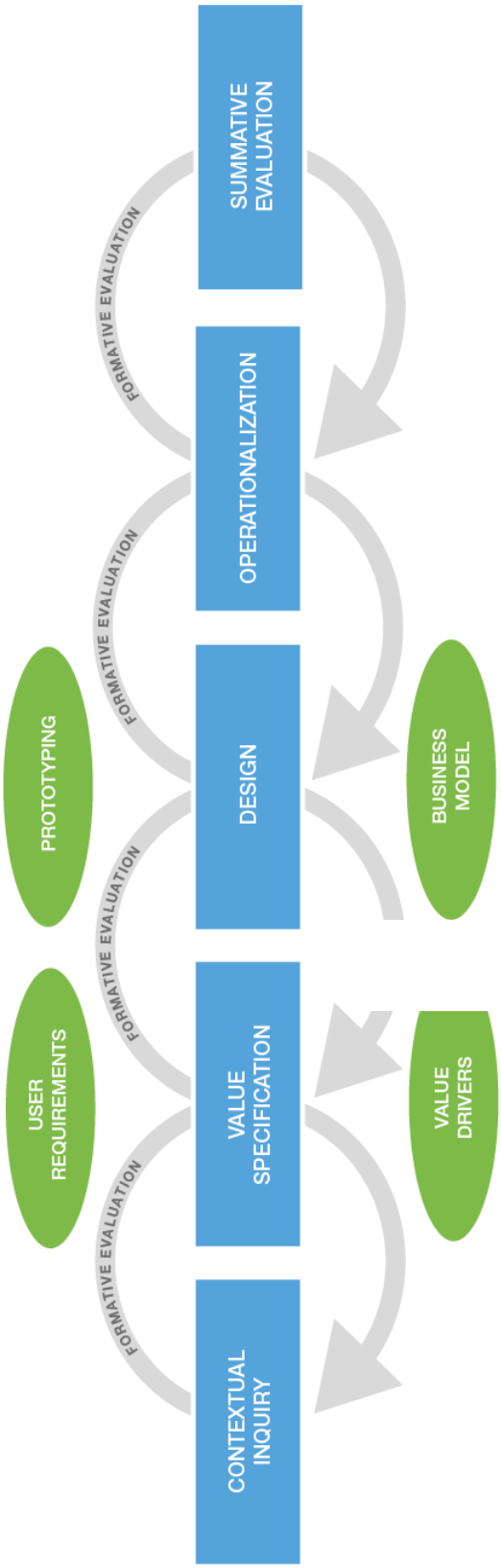


Figure 53 The Centre for eHealth and Wellbeing Research (CeHRes) Roadmap outlining the iterative development process for digital health technologies. The framework emphasises continuous formative evaluation at each stage, culminating in a final summative evaluation that compares the developed solution against the original user requirements and intended outcomes (van Gemert-Pijnen et al., 2011)

7.2. Participants

This study was conducted under ethical approval from the Strathclyde University Ethics Committee (protocol number UEC24/108 Kerr; Appendix 13).

Participants who were already attending the TERG (Kerr et al., 2023), and had given consent to participate in rehabilitation technology development, including the DAIM, were the invited to participate, following the eligibility criteria listed below.

The inclusion criteria included: (1) people able to communicate in English (oral, reading and writing); (2) individuals who are discharged from hospital; (3) those who have access to the internet; (4) those who have an email address; (5) those who are familiar with smartphones and accompanying mobile applications e.g. owns an iPhone or Android mobile; (6) people who can provide informed consent; (7) individuals who are able to follow simple 4-word instructions in English; (8) participants must also be members of a CHSS support group in Glasgow.

The exclusion criteria were: (1) those who cannot provide written, informed consent; (2) people who have a history of falls; (3) those who do not do any physical rehabilitation.

To recruit these participants, a visibly accessible recruitment poster was placed in the waiting area of the Co-creation centre and email advertisements were distributed to those who had previously taken part in the TERG (and had stated that they would be interested in future studies). Prior to participating at the TERG a consent form had to be signed in which participants consented to being contacted to partake in future studies.

Participants were given five days to read the PIS and if they wanted to participate, then they would contact the lead investigator (Boyd) and return a hand-signed and dated consent form, an electronic method of signing was also available. If a participant had received a copy of the PIS sheet and had not responded after 10 days, the individual would be contacted again to

answer any questions raised and determine their willingness to participate. As participants were recruited from those participating in the TERG study, this meant that they had already been assessed for capacity to consent via screening by a physiotherapist, allied health professionals, and completing a Montreal Cognitive Assessment (MoCA).

7.3. Methods

Participants were required to attend two 1-hour sessions at the Weston Gait Laboratory in the Wolfson Centre at the University of Strathclyde, one at the start of the study and one a week later. Both sessions were conducted solely between the participant at the time and the researcher, to allow the participant to be comfortable and ask any questions they may have. The purpose of the first session was a guided demonstration of the DAIM system, this included assisting the participant through the process of putting on and removing the intensity tracker, demonstrating how the dosage system interacted with the mobile phone app and how to operate the mobile phone and accompanying app, then allowing the participant to practice using the device and then assessing whether the participant could use the DAIM system independently.

Once the participant felt confident in using the system, they were then instructed to create a profile on the app and answer the app's survey to give them personalised daily tasks to complete. The creation of this app also created their unique identifier (UID) and Group ID, to link up the DAIM's dosage system their UID was then paired to the main server in the Gait Lab which would track their exercises within the lab when they came to the rehab sessions.

Prior to this investigation, all members of the TERG rehabilitation cohort (n=9) were introduced to the DAIM dosage system as part of their induction. This allowed any potential participants in the DAIM study to become accustomed to using the system. It also acted as a method of data collection for the TERG study after the system had been validated clinically as per Section 4.5.

Once each participant's profile on the app was created, they were instructed to take the mobile phone and intensity tracker home for a minimum of seven days. Participants were asked to use the DAIM system at least twice while at home and during every visit to the TERG during this time-period. Using the DAIM system at home involved (1) completing assigned daily tasks at home and (2) accessing the community feature to monitor the group's progress.

To investigate the secondary aims of the study, participants were made aware of the competitive leaderboard displayed during TERG sessions on a monitor in addition to the cooperative group feature of the app. This leaderboard recorded each participant's unique identifier (UID), their activity time history: including the equipment used, the duration of use (in hours, minutes, and seconds), and their total cumulative rehabilitation time.

Participants would be contacted either in person during a TERG session or via phone 3 days after taking the system home to check-up on the participant and answer any additional questions that they may have.

After the 7-day period was finished, participants were invited back for their second 1-hour session in which they would then complete three surveys: SUS, the IMI, and UEQ. This was followed by an approximately 30-minute semi-structured interview.

7.3.1. Questionnaires

All three questionnaires (SUS, IMI and UEQ) used in this study are well established in both digital health and rehabilitation research to assess usability, user motivation and overall user experience (Section 4.3.3.4 & Section 4.4.3.6). By including all three questionnaires the evaluation of the DAIM covers the multi-factorial nature of usability. These questionnaires are also consistent in multiple instances of the codesign process and aligns with best practise methods in user-centred design, by ensuring that the end-user feedback is captured in a

quantifiable and credible manner (Takano et al., 2023). Additionally, all three questionnaires do not require a license to administrate them.

7.3.1.1. User Experience Questionnaire (UEQ)

The UEQ is a standardised method to measure the broader UX of a system. Whilst the SUS focuses on usability and IMI on motivational state, the UEQ captures users' holistic impressions, including both pragmatic qualities and hedonic qualities (Laugwitz et al., 2008; Schrepp, 2023). The UEQ was designed to allow for quick assessment of the UX with the most amount of detail (Hinderks et al., 2019; Laugwitz et al., 2008). The UEQ consists of 26 items on a 7-point scale which act as semantic differentials (e.g. "Annoying - Enjoyable") that are grouped into six scales: attractiveness, perspicuity, efficiency, dependability, stimulation and novelty (Appendix 9). With these scales the UEQ can provide a comprehensive profile of the codesigned system.

To score the UEQ, each item directly corresponds to a numerical value where responses on the left side are negative (–3, –2, –1), neutral (0), and on the right side positive (+1, +2, +3) (Laugwitz et al., 2008). For each item, a transformation is applied based on whether the item is reversed or not. This is given by:

$$s_i = \begin{cases} r_i - 4, & if\ the\ item\ is\ not\ reversed \\ 4 - r_i, & if\ the\ item\ is\ reveresed \end{cases}$$

where r_i is the response (on a 1–7 scale) for item i and s_i is the transformed score on the –3 to +3 scale.

To derive the average score for each UEQ section, the numerical responses for items belonging to that subsection are summed and then divided by the number of items within that subsection. This is expressed as:

$$imension\ Score = \frac{\sum_{i=1}^{n} s_i}{n}$$

where n is the number of items in that subsection. For example, if a UEQ subsection (e.g., Attractiveness) includes 6 items, the average score is calculated as:

$$Attractiveness = \frac{s_1 + s_6 + s_{11} + s_{16} + s_{21} + s_{26}}{6}$$

Table 36 details all the items categorised into each dimension.

Table 36 UEQ subscales(Schrepp et al., 2017).

Dimension	**Items**	**Number of Items**
Attractiveness	1, 12, 14, 16, 24, 25	6
Perspicuity	2, 4, 13, 21	4
Efficiency	9, 20, 22, 23	4
Dependability	8, 11, 17, 19	4
Stimulation	5, 6, 7, 18	4
Novelty	3, 10, 15, 26	4

The resulting scores therefore range between −3 (extremely poor) and +3 (extremely good), with positive scores (>0) indicating a positive evaluation, scores around 0 suggest neutral user perception and negative scores (<0) indicating a negative evaluation.

The UEQ handbook also recommends that a derived scale to interpret standard deviation results in large sample studies, with <0.83 indicating high agreement, 0.83-1.01 showing medium agreement and >1.01 indicating low agreement. The UEQ handbook also offers three clear

benchmark datasets, one general benchmark and two for special product types (Table 37) to allow for straight forward interpretation and design improvements.

Table 37 UEQ General Benchmark (Schrepp et al., 2017).

Benchmark Category	Range of UEQ Mean Scores
Excellent	≥ +1.6
Good	≥ +1.12 to < +1.73
Above Average	≥ +0.7 to < +1.2
Below Average	≥ +0.16 to < +0.78

The UEQ, similar to the SUS and IMI, is a standard method of measurement in health technology (Takano et al., 2023). For example, one study utilised the UEQ to assess a virtual coaching system for neurological rehabilitation, reporting positive user experiences among stroke survivors and Parkinson's patients (Seregni et al., 2021). Likewise, another study applied the UEQ alongside the SUS to evaluate a digital platform for orthopaedic rehabilitation, finding excellent scores across all user experience dimensions (Papadopoulos et al., 2024). In stroke rehabilitation specifically, studies have used the UEQ to confirm high patient acceptance and usability of an augmented reality home-based rehabilitation system (Yang et al., 2022). The UEQ has also demonstrated a high internal consistency (Cronbach's alpha = 0.7-0.9) and so is regarded as a reliable and accurate method of measurement (Schrepp et al., 2017).

7.3.2. Semi-structured Interviews

Following the completion of the surveys, participants were interviewed by the researcher. Interviews were conducted on a one-to-one basis in a quiet room. Interviews were semi-

structured in nature with questions aimed to encourage a discussion with the participant (Semi-structured Interview Question Schedule).

The structure and content of the interview guide were informed by prior qualitative research evaluating stroke rehabilitation technologies that has used semi-structured interviews to explore participants' rehabilitation background, experiences of system use, usability, motivation, social support, and intention for continued use following a defined intervention period (Chen et al., 2020; Spits et al., 2024). Consistent with this approach, the present interview guide was structured to first contextualise participants' stroke and rehabilitation experiences, before eliciting detailed feedback on specific system components (wearable intensity tracker, NFC-based dosage tracker, and mobile application), and concluding with overall reflections on perceived benefits, challenges, and future use of the DAIM system after one week of real-world use (Chen et al., 2020).

Questions were split into five sections: (1) participants experience with stroke rehabilitation technology, (2) feedback from using the intensity tracker, (3) feedback from using the dosage tracker, (4) feedback from the mobile phone application, including the community feature and (5) overall feedback of the DAIM system. All interview questions are available in Appendix 10.

7.3.3. Reflexivity

In conducting this study, the researcher's position and philosophical stance were considered to improve transparency and rigor. Ontologically, this study adopts a constructivist perspective, recognising that participants' experiences of stroke rehabilitation and technology use are subjective, socially situated, and influenced by individual context (Charmaz, 2017). Epistemologically, the researcher acknowledges that knowledge is co-constructed through interaction with participants and the insights generated reflect both the participants'

perspectives and the researcher's interpretation of these experiences (Urcia, 2021). As the primary facilitator of the DAIM systems' evaluation, the researcher was directly involved in demonstrating the system, guiding participants through its use, and conducting interviews, which may have influenced participant responses through relational dynamics, framing of questions, or non-verbal cues (Dodgson, 2019). Reflexive practices, including maintaining field notes, documenting decision-making processes, and iterative discussion with a research physiotherapist were used to critically examine how the researcher's background, assumptions, and prior involvement in the co-design of the DAIM system could shape data interpretation (Ahlness & Mog, 2025). By explicitly acknowledging these factors, the study aims to provide a transparent account of each user's experience and interpretation with the DAIM system and for the researcher to place these findings within the broader context of the co-design technology evaluation.

7.3.4. Data Management and Analysis

Participant demographics (age, time since stroke, sex, hemiplegic side, aphasia, orthotic device) were collected at the start of the study. Data collected to measure the system's usability and subjective experience consisted of multiple surveys including SUS, IMI and UEQ. Participant's adherence to their daily goals and collaborative community feature were exported from the online server (expanded in Section 6.2.5) and the daily steps and cycle reps were exported from the mobile phone app after each participant had returned the mobile phone. Interviews were audio recorded, then transcribed and analysed using NVivo qualitative analysis software (NVivo, QSR International, Melbourne, Australia).

7.4. Results

This results section presents findings from both quantitative survey data and qualitative semi-structured interviews, offering a comprehensive overview of participants' experiences with the

DAIM system. Section 1 of the interviews explores the contextual background of each participant, focusing on their personal experiences with stroke rehabilitation, prior use of rehabilitation technology, and regular rehabilitation routines. Sections 2 to 5 concentrate on the design, usability, and functionality of the DAIM system.

From the total cohort (n=9) nine were approached to participate, three agreed and six declined due to uneasiness around using mobile phones (n=2) and having prior commitments (n=4). Participants will be described in detail in each of the case studies below.

As this study follows a case study approach involving three participants, each participant's interview responses are presented alongside their corresponding survey results. This is followed by a group analysis of the quantitative results across all participants and concludes with a summary of key findings.

7.4.1. Participant One

Participant One was a 29-year-old female with right-sided hemiplegia and aphasia resulting from a stroke that had occurred 15 months prior. She ambulated with the assistance of an Ankle Foot Orthosis (AFO). Throughout her time at the TERG rehabilitation sessions, she used the dosage tracking component and began using the full DAIM system during the sixth week of her rehabilitation. She attended three TERG sessions over the course of the investigation and used the system at home X times. She was assigned a UUID and was grouped with Participant 2 for the community feature as per the server requirements (Section 6.2.5).

7.4.1.1. Interview – Background

In her interview, Participant One stated that they had suffered from a haemorrhagic stroke two years previously, currently uses an AFO to walk and had exhausted all their NHS provided rehabilitation. The participant also identified that she has taken-up private physiotherapy and plans to continue it after the study. Apart from the TERG, she had never participated in stroke

rehabilitation research. Her current rehabilitation routine included a frequent combination of standard upper and lower limb movement routines that had been prescribed by their private and NHS physiotherapists.

The participant's current rehabilitation goals were to improve her movement speed and regain more movement in her affected upper limb. The participant also explained that she was familiar with some rehabilitation technology, having used a FitMe robotic hand glove at home in parallel with a movement home-based rehabilitation technology (Swanson et al., 2023)). When asked about her thoughts on these technologies she had used at home, the participant explained that whilst the FitMe was good on paper, she felt that she did not recover as much as she had hoped. When questioned about the robotic glove, the participant felt that the glove was only good for stretching and massaging her hand and did not indicate that she felt she received any rehabilitation from the device.

7.4.1.2. Interview – Intensity tracker

Participant One described the experience with the wearable tracker as generally positive, particularly due to its discrete size, noting,

"The device is small and you kind of forget about it."

She found that frequent adjustments to the thigh tracker were irritating, describing the discomfort as "constantly pulling it back up was a little bit annoying." The main challenge was the thigh strap slipping due to the material of her leggings which caused regular adjustments, as the participant remarked,

"I felt like the strap was falling down a lot."

The participant found that her motivation was influenced by the step counter, as it highlighted her household movement patterns, which further prompted her,

"to lift the knee and focus on my foot."

The participant found the data collected helpful, observing that the thigh tracker seemed more sensitive than her phone tracker, noting it recorded,

"a lot more steps than I thought."

No Bluetooth connectivity issues were reported.

7.4.1.3. Interview – Dosage tracker

Participant One found the NFC tracker straightforward to use, saying that the primary challenge was remembering to bring the card to each station, stating,

"The cards were easy, I just had to remember to take them with me."

She reported that it took approximately three sessions to consistently remember the card. The participant found that the dosage tracking device itself was helpful in pushing her to maximise her rehabilitation time but did not alter her commitment, as she had already described herself as a dedicated person during rehabilitation activities. The participant appreciated the competitive aspect, remarking,

"The gym that I used to go to had these sort of challenges and that motivated me too."

There were no functionality issues except occasionally needing to switch the dosage tracker on if it had not been turned on. The participant felt the dosage information collected was accurate and helpful.

7.4.1.4. Interview – App

Participant One found the app supportive and motivating, particularly appreciating the goal-setting feature, stating,

"Having a target named activity is motivating like 'walk 100 steps'."

She thought the app's interface was straightforward, though expressed a desire for more challenging and diverse goals. Participant One also felt pressure from the community feature, noting,

"If somebody else was meeting their targets and I had not, then I would feel pressure like I had let the team down."

Participant One frequently referred to the suggested rehabilitation tasks throughout the week but also desired additional and longer tasks. She found that the 'Notes' feature (Section 6.4.5) which allowed a user to freely document any additional movement tasks, helped her to feel more informed about their rehabilitation progress as she could log unique activities (e.g. housework).

7.4.1.5. Interview – Closing Questions

Participant One identified the thigh tracker and app as the most beneficial tools in her rehabilitation experience, emphasising its supportive potential:

"Coming out of the hospital, you feel very on your own… the thigh tracker and the app would have felt like more community."

She specifically suggested improvements to the thigh tracker for enhanced comfort and usability and expressed a clear interest in using the system long-term.

7.4.1.6. Survey results

Participant One recorded a SUS score of 80 out of 100, which equates to a B+ on the curved benchmark and falls five points below the 'excellent' threshold on the Bangor usability scale.

The IMI produced a total score of 5.00 out of 7, representing a moderate-to-high level of motivation. As observed in existing literature, a consistent pattern of high Interest/Enjoyment,

high Perceived Competence, high Perceived Choice, and low Pressure/Tension emerged. Detailed scores are provided in Table 38.

Table 38 Participant One IMI results

Dimensions	Participant One	Result
Interest / Enjoyment	6.00	High degree of inherent interest and pleasure the participant has found using the DAIM.
Perceived Competence	6.00	High sense of competence in using the DAIM.
Effort / Importance	5.67	High effort and value the participant has placed on the DAIM.
Pressure / Tension	1.00	Low feelings of pressure, stress or tension felt when using the DAIM.
Perceived Choice	4.67	Moderate feelings of autonomy.
Value / Usefulness	6.00	High perception of the DAIM's practical value.
Total IMI score	5	Moderate/High

Participant One's UEQ results, displayed in Table 39, indicate a generally positive user experience, with most dimensions reaching the 'Excellent' benchmark. Novelty was rated as 'Above Average'.

Table 39 Participant One UEQ results

Dimensions	Participant One	Benchmark
Attractiveness	2.00	Excellent
Perspicuity	3.00	Excellent
Efficiency	1.75	Good
Dependability	2.50	Excellent
Stimulation	2.50	Excellent

Novelty	0.75	Above average

7.4.1.7. Movement Data

Participant One's weekly movement data are summarised in Table 40. The participant completed daily goals on three occasions, and her designated team ended the week with a 3-level tower, indicating that all group members completed their daily goals on three days (Figure 55).

Table 40 Participant One movement data from intensity tracker

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Step reps	0	178	0	0	243	111	0	532
Cycle reps	0	246	0	0	225	260	0	731
Sit-to-stand reps	0	15	0	0	11	10	0	36

Figure 54 shows an entry from the server database (phpMyAdmin) during Participant One's use, illustrating an example where Participant Two completed their daily goals, while Participant One had missed two consecutive days. This provides insight into individual and group adherence patterns.

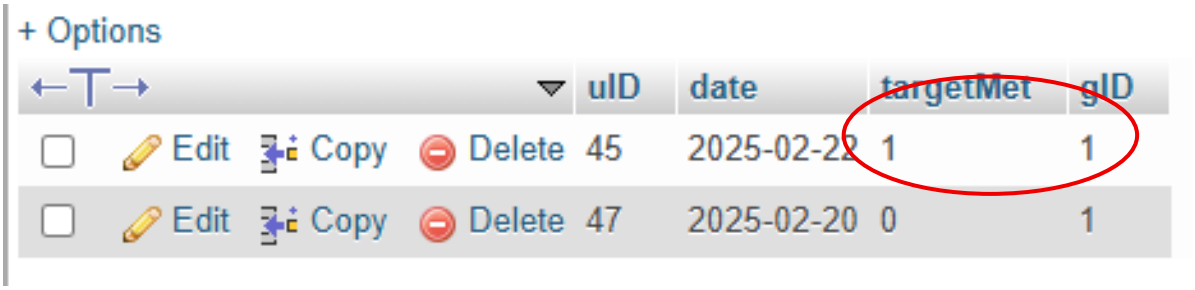


Figure 54 phpMyAdmin screenshot showing a sample entry from a day when Participant Two had completed a daily task, while Participant One had not completed their goals for two consecutive days (0 = not complete, 1 = complete).

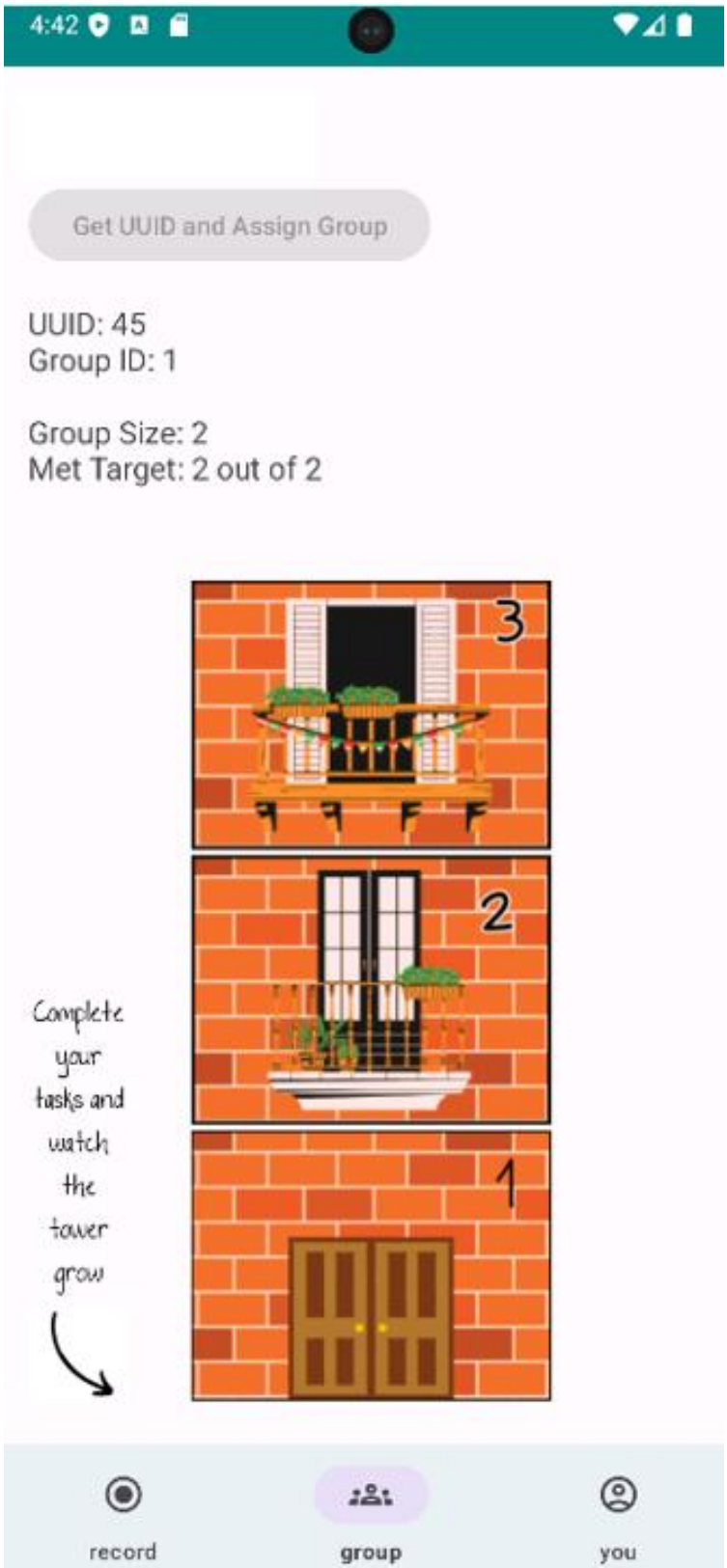


Figure 55 Screenshot of final view of Participant One's community feature showing a 3-level tower

7.4.1.8. TERG Rehabilitation Sessions

Participant One engaged in 40 hours and 4 minutes of active rehabilitation during the TERG sessions, the highest recorded among all nine participants. Details of equipment usage, session frequency, and time variance are presented in Table 41.

Table 41 Participant One Dosage data breakdown

Workstation Category	Equipment	Number of Uses (n)	Total Time on Equipment (minutes)	Mean Difference of Manual vs Digital (minutes) ± SD
Cable and Squats	Cable machine, Squat machine (Motek Medical, Netherlands)	19	321.12	17.50 ± 18.44
Balance games	MR Cube Monitored Rehab Tool (Metler Electronics Corp, US), and Oculus Meta Quest 2 VR headset (Meta, US)	16	331.08	20.69 ± 14.31
Treadmill	C-Mill (Motek Medical, Netherlands)	16	456.00	28.50 ± 24.82
Power Assist Equipment	Cross cycle, Chest & Legs, and Seated Climber devices (Innerva, UK), MOTOmed Loop.p.la exercise bike (MRS, UK)	19	300.82	15.83 ± 8.76
All Equipment Uses	All above-listed equipment (excluding gym attendance)	70	1409.02	20.29 ± 17.62
Total Time Spent in Rehabilitation Gym	Attendance in gym	18	1030.17	57.23 ± 26.36
Overall	**-**	**88**	**2439.18**	**27.95 ± 7.32**

7.4.1.9. Participant Feedback

Participant One offered feedback during the TERG sessions:

- "I do think it is a bit bulky, but I like the goals aspect of it. It stops me from fannying about when I'm doing my rehab and will make me actually try harder."
- "I think of it like a template, like a gym template."

This feedback suggests that while the physical design could be improved for comfort, the participant often wore leggings which are typically made of blends of polyester, nylon, and spandex. Suggesting that these materials could be incompatible with the DAIM intensity tracker.

7.4.2. Participant Two

Participant Two was a 47-year-old male with left-sided hemiplegia following a stroke 24 months prior. He used the dosage tracking component during his participation in the TERG rehabilitation sessions and began using the full DAIM system in the sixth week of rehabilitation. He attended four TERG rehabilitation sessions during the DAIM study and also used the system at home. He was assigned a UUID and was teamed with Participant One for the community feature.

7.4.2.1. Interview – Background

Participant Two reported experiencing a stroke in March of 2023. Initially, his rehabilitation progressed effectively until he sustained an injury to his right shoulder due to physiotherapy, after which he felt neglected by NHS rehabilitation services. Participant Two explained that he had not paid for any private physiotherapy or participated in experimental rehabilitation previously. Due to his health-oriented mindset, he independently pursued intensive exercises

at home when his NHS support decreased. The participant described himself as very self-motivated and he was determined to regain his mobility in both his upper and lower limbs.

The participant described his current rehabilitation routine as driven and proactive, highlighting again his persistence and motivation. His current rehabilitation goal involved improving his upper limb functionality, specifically regaining the ability to fully extend his arm and effectively use his hand and to get back to using his bicycle.

Regarding rehabilitation technology usage, Participant Two mentioned previously using fitness-tracking devices, like a Fitbit step counter, prior to his stroke but had not considered using these tools for his rehabilitation until using the DAIM system.

7.4.2.2. Interview – Intensity tracker

Participant Two found the wearable tracker highly motivating and described it as positively influencing his activity levels, stating,

"it pushed me to the point I actually got the bike out the garage again."

Acknowledging his hemiplegic side, Participant Two emphasised how the tracker pushed him to be more active in his walking, stating that the tracker felt

"like a third person sitting there saying 'get up and get this done'."

Challenges around the tracker included intermittent connectivity issues outside university premises, described as "a server issue", however this did not stop him from completing his daily tasks. Although generally comfortable, the participant suggested improvements to the design, recommending making it "a wee bit more slim-lined" and incorporating "some sort of storage device" to enhance data reliability. Participant Two found the collected data very useful in determining his activity levels, clearly indicating when he was

"being lazy as opposed to being active." Minor Bluetooth connectivity issues were regarded as initial "teething problems."

7.4.2.3. Interview – Dosage tracker

Participant Two described the NFC tracker as very user-friendly, although highlighted slight cognitive challenges, particularly with short-term memory issues, as the main difficulty stating, *"Our short-term memory is not amazing… so it's the constant reminder."*

The participant said that after about two sessions they felt more comfortable using the dosage tracker. Participant Two felt that the system pushed him to complete more rehabilitation activities, driven by the awareness of the data collection and subsequent feedback:

"Knowing at the back of my mind that all this data is getting collected… was definitely motivational."

He recommended making the NFC system mandatory for TERG sessions, emphasising its potential to motivate people, even those less driven. The participant found the NFC responsiveness reliable and simple to use and felt that the dosage information collected was accurate.

7.4.2.4. Interview – Mobile phone App

Participant Two described their experience using the app as largely positive, finding the app easy to navigate despite the connectivity issues. He believed the goal-setting feature was very beneficial but not sufficiently challenging enough, suggesting more defined difficulty levels ("beginner, intermediate and expert") to better reflect varied fitness levels. Participant Two enjoyed the community feature but suggested pairing participants by their similar motivation levels:

"It would maybe be better to pair people up that is just as driven as you."

Participant Two further explained that sometimes,

"I was looking at the tasks completed bit, and I was thinking 'come on other participant'."

Participant Two consistently engaged with app tasks, suggesting these could better reflect typical gym routines or gym plan. Overall, he found the app helpful for conveniently monitoring progress.

7.4.2.5. Interview – Closing Questions

Participant Two highlighted both the thigh tracker and the app as highly beneficial, particularly valuing how the tracker encouraged his cycling activity:

"It got me out cycling."

He recommended improvements primarily to the app to enhance its functionality and expand on the goals level of difficulty. Overall, Participant Two found that the DAIM system boosted their motivation and rehabilitation support and showed definite interest in continuing to use the system long-term.

7.4.2.6. Survey results

Participant Two recorded a SUS score of 90 out of 100, corresponding to an A on the curved benchmark and placing the DAIM system five points above the 'excellent' threshold on the Bangor usability scale.

The IMI produced a total score of 6.15 out of 7, showing high user motivation and engagement. As with the previous participant, the data demonstrated a consistent pattern of high Interest/Enjoyment, high Perceived Competence, high Perceived Choice, and low Pressure/Tension. A detailed breakdown of scores is provided in Table 42.

Table 42 Participant Two IMI results

Dimensions	Participant Two	Result
Interest / Enjoyment	7.00	High degree of inherent interest and pleasure the participant has found using the DAIM.
Perceived Competence	6.67	High sense of competence in using the DAIM.
Effort / Importance	6.33	High effort and value the participant has placed on the DAIM.
Pressure / Tension	3.00	Low feelings of pressure, stress or tension felt when using the DAIM.
Perceived Choice	6.67	High feelings of autonomy.
Value / Usefulness	6.75	High perception of the DAIM's practical value.
Total IMI score	6.15	High

Results from the UEQ summarised in Table 43, show a consistently excellent user experience across all measured dimensions. Each score exceeded benchmark averages, highlighting a very positive user experience of the DAIM system.

Table 43 Participant Two UEQ results

Dimensions	Participant Two	Benchmark
Attractiveness	2.17	Excellent
Perspicuity	3.00	Excellent
Efficiency	2.75	Excellent
Dependability	2.50	Excellent
Stimulation	2.75	Excellent
Novelty	2.00	Excellent

7.4.2.7. Movement Data

Participant Two's physical activity data over a one-week period is shown in Table 44, reflecting engagement across all steps, cycle, and sit-to-stand tasks. The participant successfully completed daily goals on five occasions. Despite this high individual adherence, the team total resulted in a 3-level tower, indicating three days where all group members completed their daily goals.

Table 44 Participant Two movement data from intensity tracker

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Step reps	0	0	126	123	201	258	277	985
Cycle reps	0	0	2775	0	197	858	767	4597
Sit-to-stand reps	0	0	4	10	10	13	15	52

7.4.2.8. TERG Sessions

Participant Two accumulated 18 hours and 35 minutes of active rehabilitation during the TERG rehabilitation sessions, ranking 4th out of 9 participants. Equipment use, duration, and time variance are detailed in Table 45.

Table 45 Participant Two Dosage data breakdown

Workstation Category	**Equipment**	**Number of Uses (n)**	**Total Time on Equipment**	**Mean Difference of Manual vs Digital (minutes) ± SD**
Cable and Squats	Cable machine, Squat machine (Motek Medical, Netherlands)	11	228.12	20.74 ± 15.29
Balance games	MR Cube Monitored Rehab Tool (Metler Electronics Corp, US), and Oculus Meta Quest 2 VR headset (Meta, US)	5	54.08	10.82 ± 6.41

Treadmill	C-Mill (Motek Medical, Netherlands)	11	127.78	11.62 ± 8.15
Power Assist Equipment	Cross cycle, Chest & Legs, and Seated Climber devices (Innerva, UK), MOTOmed Loop.p.la exercise bike (Medimotion, UK)	11	113.92	10.36 ± 5.40
All Equipment Uses	All above-listed equipment (excluding gym attendance)	38	523.90	13.79 ± 10.67
Total Time Spent in Rehabilitation Gym	Attendance in gym	11	614.43	55.86 ± 17.38
Overall	**-**	**49**	**1138.33**	**21.88 ± 5.44**

7.4.2.9. Participant Feedback

Participant Two provided positive feedback during the TERG rehabilitation sessions, highlighting both enjoyment and motivation:

- "I thought it was really good and I really liked the goals aspect of it."
- "I'm dead competitive and it makes me want to work hard."
- "I want to use it every day."

He also reported occasionally selecting the "*I am not at Strathclyde today"* button (Section 6.4.2) after completing all available goals to generate new ones, suggesting that the goal targets may not have been challenging enough for his ability level. Additionally, the participant commented that the DAIM system motivated him to use his bicycle and increase outdoor activity, as he became more aware of his physical output.

7.4.3. Participant Three

Participant Three was a 63-year-old male with right-sided hemiplegia resulting from a stroke that had occurred 21 months earlier. He used the dosage tracking component throughout the TERG rehabilitation sessions and began using the full DAIM system during his eighth week of rehabilitation. He attended two TERG rehabilitation sessions during the investigation and used the system at home. He was assigned a UUID but did not have a peer to engage with through the community feature. As a result, the researcher assumed the role of a fellow stroke rehabilitation user to simulate the community aspect.

Due to hardware limitations, specifically, the availability of only two fully functional wearable prototypes, only two participants could take part in the study at a time. When it was time for Participant Three to begin, the existing teams were reset to prevent him from being grouped with previous users who were no longer active. This ensured that the group-based visual feedback, such as progress in the shared tower display, remained meaningful and responsive to current activity.

7.4.3.1. Interview – Background

In his interview, Participant Three reported multiple stroke events, starting with a TIA which was then followed by an additional TIA, then two further ischaemic strokes. Following the second stroke, an operation was performed in which he encountered complications, resulting in an extended hospital stay. Post-discharge, he received eight home NHS physiotherapy sessions from the community stroke team, followed by outpatient physiotherapy at Victoria Hospital, which he found challenging due to significant pain in his arm. Participant Three had also not purchased private physiotherapy or participated in any rehabilitations research programmes.

Participant Three's current rehabilitation goals were focused on improving his quality of life, highlighting a desire to regain the ability to drive, and assist with gardening. Participant Three had also previously used a TENs machine for pain, reporting mixed experiences due to difficulties adjusting settings, balancing between ineffectiveness and discomfort. Additionally, he received a mirror glove as a Christmas gift, which he continues to use regularly but does not see much of an improvement.

7.4.3.2. Interview – Intensity tracker

Participant Three reported an overall positive experience with the wearable device, initially frequently checking its functionality, stating,

"I did keep looking down all the time to see if it's still working."

He also encountered a slight challenge when independently fitting the device due to limited mobility in his left hand, noting,

"Putting it on was a wee bit challenging."

He suggested an "extension cord" or "a belt with the holes in it" to improve ease of use. The participant had also expressed some initial confusion regarding the cycling revolution data as he did not understand what 'one rep' meant. This was clarified during the initial follow-up, helping him to better understand the information. While finding the device mostly comfortable, he mentioned it "could have been a wee bit lighter," attributing slight discomfort to the battery size. No Bluetooth connectivity issues were experienced.

7.4.3.3. Interview – Dosage tracker

Participant Three considered the NFC tracker easy to use after initial adaptation, taking "two sessions" to him to become accustomed. His primary challenge was occasionally forgetting to

tap in, which meant that the system wouldn't have recognised what activity he had taken part in, recalling,

"It happened the other day on the treadmill and it destroyed me because I forgot."

The participant found the NFC tracking helpful in maintaining focus on his rehabilitation goals, saying that it aided motivation. Occasional responsiveness issues did occur with the dosage system, however he noted that they were resolved promptly. The participant viewed the dosage information as accurate, noting that personal differences in interest levels could affect this and did not think of the leaderboard as competitive.

7.4.3.4. Interview –Mobile Phone App

Participant Three described his overall app experience as straightforward, noting the ease in navigation and accessibility of information:

"You can see what information you wanted…then act accordingly."

The Goal-setting feature was one of his favourites aspects as it allowed him to feel a sense of accomplishment upon reaching his targets. The participant also valued the community feature and preferred the cooperative approach, stating,

"You're trying to help…the other persons had their stroke so I need to try and help them."

He suggested tailoring tasks more specifically to the individual rehabilitation needs, such as focusing on particular limbs. The app was also noted to effectively help him remain informed and in control of his rehabilitation progress.

7.4.3.5. Interview – Closing Questions

Participant Three found the community feature of the app and the dosage tracker as the most beneficial. He also found that all the components of the DAIM increased his sense of support

in his rehabilitation journey, leading to an enthusiastic willingness to adopt similar products in the future, amusingly noting that,

"If it came in the market and it was on Amazon, yes, I would order it from Amazon, Next day delivery."

7.4.3.6. Survey results

Participant Three's SUS score was 80 out of 100, corresponding to a B+ on the curved grading benchmark and placing the DAIM system just five points below the 'excellent' category on the Bangor usability scale.

The IMI produced a total score of 5.75 out of 7, indicating a high level of user engagement and positive motivation. A detailed breakdown of Participant Three's IMI results is provided in Table 46. As with previous findings, a pattern of high Interest/Enjoyment, high Perceived Competence, high Perceived Choice, and low Pressure/Tension was observed.

Table 46 Participant Three IMI results

Dimensions	Participant Three	Result
Interest / Enjoyment	6.75	High degree of inherent interest and pleasure the participant has found using the DAIM.
Perceived Competence	6.67	High sense of competence in using the DAIM.
Effort / Importance	6.00	High effort and value the participant has placed on the DAIM.
Pressure / Tension	1.00	Low feelings of pressure, stress or tension felt when using the DAIM.
Perceived Choice	7.00	High feelings of autonomy.

Value / Usefulness	6.50	High perception of the DAIM's practical value.
Total IMI score	5.75	High

Whilst the UEQ does not yield a single overall score, but the dimension-specific results for Participant Three, shown in Table 47, reveal a broadly positive user experience. Most dimensions reached the 'Excellent' benchmark, with Novelty rated as 'Above Average'.

Table 47 Participant Three UEQ results

Dimensions	Participant Three	Benchmark
Attractiveness	2.00	Excellent
Perspicuity	2.25	Excellent
Efficiency	1.75	Good
Dependability	1.75	Excellent
Stimulation	1.75	Excellent
Novelty	1.00	Above average

7.4.3.7. Movement Data

Participant Three's physical activity during the home-based use of the DAIM system is summarised in Table 48. The participant completed daily tasks on four out of seven days. The accumulated totals indicate engagement with stepping, cycling, and sit-to-stand tasks, with 1,075 step repetitions, 665 cycle repetitions, and 44 sit-to-stand repetitions recorded over the week.

Table 48 Participant Three movement data from intensity tracker

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Total
Step reps	203	0	429	156	287	0	0	1075
Cycle reps	155	0	299	78	133	0	0	665

Sit-to-stand reps	7	0	16	4	17	0	0	44

As part of team, Participant Three contributed to a 4-level tower, reflecting their consistent activity. Figure 56 illustrates the app interface from the participant's perspective, showing their UUID, group ID, and the daily goal completion status of their group.

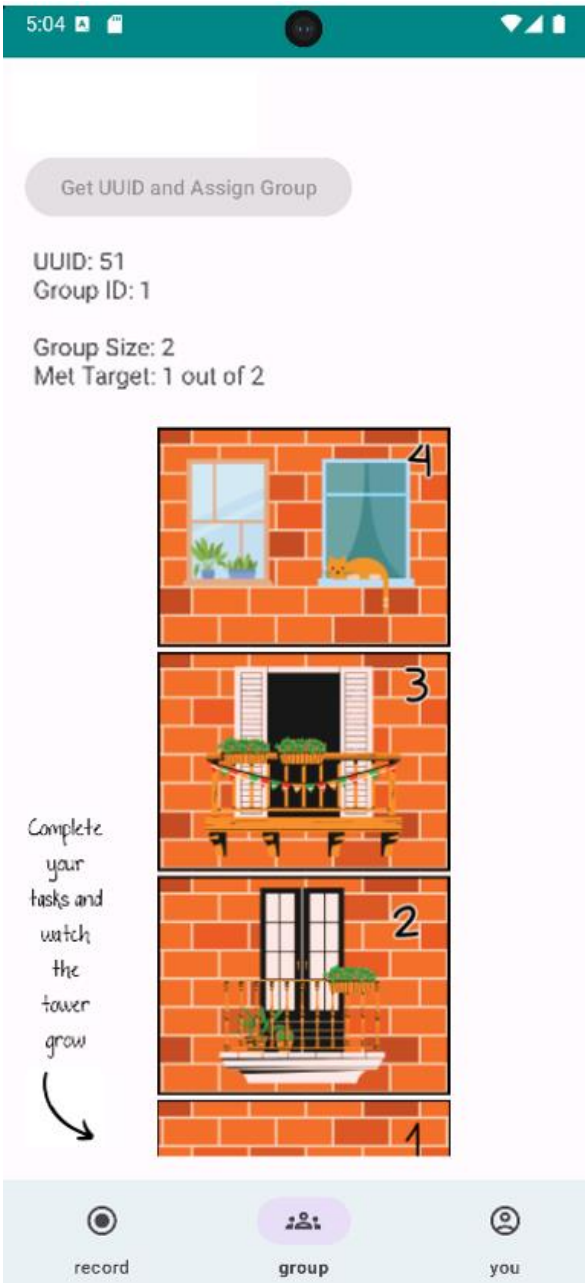


Figure 56 App interface screenshot displaying the user view. In this instance, Participant Three can see their unique user ID (UUID), group ID, and that only one member has completed their daily goals however the 4-level tower indicates that for 4 days all users had completed their personal goals.

7.4.3.8. TERG Session Participation

In the TERG rehabilitation sessions, Participant Three recorded a total of 26 hours and 28 minutes of active rehabilitation, ranking second out of nine participants for total time spent. A detailed breakdown of equipment use, total time, and variability in session duration is shown in

Table 49.

Table 49 Participant Three Dosage data breakdown

Workstation Category	Equipment	Number of Uses (n)	Total Time on Equipment	Mean Difference of Manual vs Digital (minutes) ± SD
Cable and Squats	Cable machine, Squat machine (Motek Medical, Netherlands)	15	273.45	18.23 ± 12.76
Balance games	MR Cube Monitored Rehab Tool (Metler Electronics Corp, US), and Oculus Meta Quest 2 VR headset (Meta, US)	8	73.40	6.20 ± 9.18
Treadmill	C-Mill (Motek Medical, Netherlands)	11	249.15	22.65 ± 20.41
Power Assist Equipment	Cross cycle, Chest & Legs, and Seated Climber devices (Innerva, UK), MOTOmed Loop.p.la exercise bike (Medimotion, UK)	25	456.50	18.26 ± 13.50
All Equipment Uses	All above-listed equipment	59	1052.50	17.84 ± 14.35

	(excluding gym attendance)			
Total Time Spent in Rehabilitation Gym	Attendance in gym	11	564.12	51.28 ± 18.63
Overall	**-**	**70**	**1616.62**	**23.92 ± 5.58**

7.4.4. Grouped Results

To evaluate the overall usability of the device, SUS scores from all participants were averaged, resulting in a mean score of 83.33 (SD=5.77). According to the curved SUS benchmark, this score corresponds to a B+, classified as leaning towards 'excellent' on Bangor et al.'s usability scale.

Participants' intrinsic motivation was assessed using aggregated IMI scores, with mean values summarised in Table 50.

To assess overall user experience against standard benchmarks, the UEQ scores from all participants were averaged, with results presented in

Table 51 and illustrated graphically in Figure 57.

Table 50 Mean IMI results

Dimensions	Mean participant	Result
Interest / Enjoyment	6.58	High degree of inherent interest and pleasure the participant has found using the DAIM.
Perceived Competence	6.44	High sense of competence in using the DAIM.

Effort / Importance	6.00	High effort and value the participant has placed on the DAIM.
Pressure / Tension	1.67	Low feelings of pressure, stress or tension felt when using the DAIM.
Perceived Choice	6.11	High feelings of autonomy.
Value / Usefulness	6.42	High perception of the DAIM's practical value.
Total IMI score	5.63	High

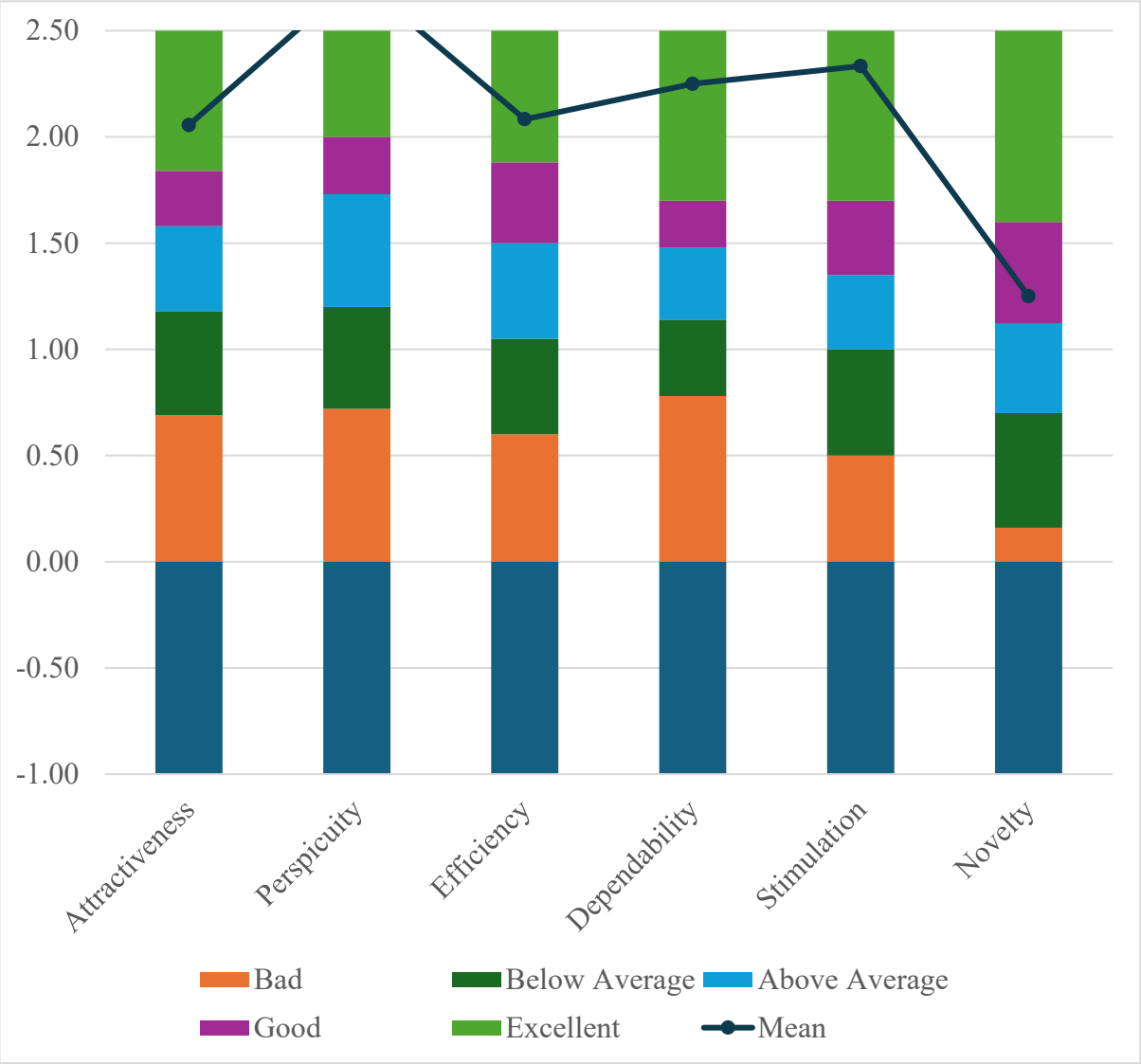


Figure 57 Graphical version of UEQ benchmarks

Table 51 Mean UEQ results comparison to benchmark

Scale	Mean	Comparison to benchmark	Interpretation
Attractiveness	2.06	**Excellent**	In the range of the 10% best results
Perspicuity	2.75	**Excellent**	In the range of the 10% best results
Efficiency	2.08	**Excellent**	In the range of the 10% best results
Dependability	2.25	**Excellent**	In the range of the 10% best results
Stimulation	2.33	**Excellent**	In the range of the 10% best results
Novelty	1.25	**Good**	10% of results better, 75% of results worse

7.5. Discussion

7.5.1. Overview and Key Findings

The aim of this study was to evaluate the acceptability and usability of the complete DAIM prototype and to compare the results to the original design requirements of the initial co-design focus group results. Overall, the DAIM demonstrated positive usability results (mean SUS=83.3) that exceed benchmarking of acceptability from multiple usability benchmarking studies (Section 7.3.1). Additionally, from a qualitative perspective the system was also found to be a positive experience for the participants as explained in their interviews, participants reported a sense of increased motivation, with individual preferences for both competitive and cooperative community features.

7.5.2. Comparison with Literature

Traditional methods of measuring rehabilitation dosage, such as paper diaries and therapist notes, have long been used in clinical practice but are prone to inaccuracies due to reliance on self-reporting and recall bias. In stroke rehabilitation, these paper-based logs are still common

but often lack validation and consistency, especially regarding intensity measures (Levy et al., 2019).

In contrast, digital solutions such as wearable sensors and rehabilitation apps have gained traction in recent research (Junaid et al., 2022). These systems can passively track movement and deliver real-time feedback. For example, commercial activity trackers have been shown to reasonably estimate intensity during stroke rehab (Kubo et al., 2022), and systems like "PrimSeq" have attempted to count upper limb repetitions with promising accuracy (Parnandi et al., 2022). These tools, however, often lack contextual information. They can record movement, but not which prescribed task was being performed, or whether it was part of a rehabilitation session. This limitation was echoed by participants in the current study, who described previous technologies as either too simplistic or lacking meaningful feedback. One participant noted that a robotic hand therapy system was "good on paper, but I didn't recover as much as I'd hoped."

The DAIM addresses these gaps by offering a dual-tracking approach. The wearable sensor captures lower-limb physical movements like steps, cycles and STS, and derive intensity metrics such as cadence, whilst the NFC tracker logs specific rehabilitation tasks, providing clarity on what was done, when, and with what intensity. This integration of movement measurement and contextual logging distinguishes DAIM from existing solutions. Unlike physiological profiling approaches that whilst captures data-rich movements at fixed time points (Ingram et al., 2021), the DAIM allows for continuous, contextual capturing of frequency, duration, and movement characteristics during unsupervised sessions across both home and clinical settings. This provides a richer representation of rehabilitation behaviour, bridging the gap between structured assessments and everyday practice.

The DAIM's usability and motivational properties, compare favourably with existing stroke rehabilitation technologies (see Table 52). The DAIM's usability scores (SUS=83.33) exceed usability scores for comparable rehabilitation technologies, such as the PLUTO hand robot (SUS = 73.3; (Nehrujee et al., 2021)) and the MERLIN upper-limb rehabilitation system (SUS = 71.94; (Guillén-Climent et al., 2021)). DAIM's IMI score (mean ~5.63) also indicates a high degree of user motivation, closely aligned with established rehabilitation systems like MERLIN (IMI = 6.12) and exceeding others like the ironHand soft-robotic glove (IMI = 5.1; (Radder et al., 2016)). Additionally, DAIM's UEQ scores (

Table 51Table 52) was categorised for user experience in the "excellent" range according to standard UEQ benchmarks, and surpassing the scores of similar rehabilitation technologies such as FriWalk robotic walker (Pérez-Rodríguez et al., 2020) (Table 52). Collectively, these results position DAIM as competitive, both in terms of technical usability and user engagement, when compared with current rehabilitation solutions.

Table 52 Comparison of SUS, IMI and UEQ scores across rehabilitation technologies. The table presents results from a range of academic studies evaluating wearable devices, robotic systems, and digital platforms used in both stroke and other forms of physical rehabilitation. Scores reflect user-reported usability, engagement, and overall user experience, with higher values indicating more favourable outcomes. The sample size for each study is included to provide additional context for interpreting and comparing reported scores.

Author / Study	Device / System	Sample Size	SUS	IMI	UEQ (Subscale Scores)
Boyd, 2025	DAIM	3	83.33	5.88	Attractiveness: 2.06
					Perspicuity: 2.75
					Efficiency: 2.08

					Dependability: 2.25
					Stimulation: 2.33
					Novelty: 1.25
(Pérez-Rodríguez et al., 2020) *FriWalk robotic walker: usability, acceptance and UX evaluation after a pilot study in a real environment*	FriWalk	14	52.86	–	Attractiveness: 1.50
					Perspicuity: 1.15
					Efficiency: 1.30
					Dependability: 1.20
					Stimulation: 1.25
					Novelty: 0.80
(Nehrujee et al., 2021) *Plug-and-Train Robot (PLUTO) for Hand Rehabilitation: Design and Preliminary Evaluation*	PLUTO – Plug-and-Train Robot	45	73.3	–	Attractiveness: 2.46
					Perspicuity: 2.30
					Efficiency: 1.45
					Dependability: 1.52
					Stimulation: 1.55
					Novelty: 1.85
(Guillén-Climent et al., 2021) *A usability study in patients with stroke using MERLIN, a robotic system based on serious games for upper limb rehabilitation in the home setting*	MERLIN (HoMEcare aRm rehabiLItatioN)	9	71.94	6.12	–

(Nijenhuis et al., 2015) *Feasibility study into self-administered training at home using an arm and hand device with motivational gaming environment in chronic stroke*	Dynamic Wrist & Hand Orthosis	21	69	5.2	–
(Radder et al., 2016) *A wearable soft-robotic glove enables hand support in ADL and rehabilitation: A feasibility study on the assistive functionality*	Wearable Soft-Robotic Glove (iH System)	28	63.4	5.1	–
(Meldrum et al., 2024) *Wearable sensor and smartphone assisted vestibular physical therapy for multiple sclerosis: usability and outcomes*	Vestibular PT System (Vertigenius + App)	12	81	–	–

(Morizio et al., 2022) *Immersive Virtual Reality during Robot-Assisted Gait Training: Validation of a New Device in Stroke Rehabilitation*	Immersive VR for Robot-Assisted Gait Training	38	86.09	–	–

Additionally, DAIM's community features, and goal setting, played a role in supporting participant engagement. Whereas paper logs typically offer no feedback, and most digital systems provide only individualised progress tracking, DAIM combines progress visualisation with cooperative and competitive elements. This appeared to enhance motivation for some users. As participant two reflected, "It pushed me to the point I actually got the bike out the garage again," illustrating how personalised, context-aware tracking can lead to increased physical activity.

7.5.3. Strengths and Limitations of the Case Study Approach

The mixed-methods case-series design used offered valuable strengths appropriate for early-stage research. By combining quantitative usability measures with qualitative semi-structured interviews, the study generated rich, detailed, and contextually informed feedback. This approach enabled a deeper understanding of individual user interactions, revealing subtle usability issues, such as confusion around interface navigation, difficulty interpreting feedback displays, and variability in user adherence, that might not have surfaced through quantitative data alone (Almojaibel, 2016; Bacchetti et al., 2011). Ethically, this strategy was appropriate as it minimised participant burden while still allowing their experiences and perspectives to be meaningfully represented. Logistically, it was manageable within the resource constraints of a

prototype evaluation yet provided sufficiently robust data to inform targeted improvements and guide future development.

The design, however, also has limitations. The sample size was small (n=3) due to the practical limitations of early-phase research (Almojaibel, 2016; Bacchetti et al., 2011), limiting the generalisability. Moreover, as participants were recruited from the TERG study (Kerr et al., 2023) that was running concurrently, there is potential selection bias as the individuals who volunteered may have been more positively inclined towards technology and motivated to engage in rehabilitation activities. Consequently, their experiences and evaluations may overstate the acceptability and usability of the system. Additionally, without a control or comparison group, definitive conclusions regarding the DAIMs effectiveness cannot be drawn. Therefore, the positive findings of this mixed-methods case series should be interpreted with caution. The insights gained are nevertheless valuable for guiding future development of the DAIM system and for designing subsequent trials. These limitations could be mitigated in the future by adopting larger, more diverse samples and rigorous designs (such as randomised controlled trials) to strengthen evidence for the system's broader applicability and efficacy when compared to other digital tools.

7.5.4. Future Iterations

Key qualitative feedback from participants primarily related to the design and functionality of the intensity tracker. Participants requested a more streamlined and market-ready appearance, specifically suggesting a reduction in battery size. Some participants (n=2), however, appreciated that the thigh tracker was rechargeable. The current design featured a larger rechargeable battery primarily due to cost-effectiveness and the practical constraints of rapid prototyping namely, limited access to custom enclosures, reliance on off-the-shelf components, and the need for modularity to allow quick changes during development. Additionally, as the

thigh tracker was handmade (assembled from individually purchased components, either stitched or glued together) the design intentionally allowed for easy breakdown and modification during development. Participants acknowledged that their suggestions would ideally be addressed in future commercial or manufactured prototypes, where a smaller, lightweight battery solution could be implemented.

The weight of the current battery contributed to the tracker occasionally slipping down the thigh, requiring participants to adjust its position during use. Despite this inconvenience, participants unanimously preferred securing the device with a Velcro strap over alternatives such as buckles, clasps, or magnets. They reported that the Velcro strap was easier to handle, particularly given their upper limb impairments. Thus, future development should focus on reducing component size and exploring alternative materials or strap designs to enhance grip on various clothing types. Participants wore different trousers (including jeans, leggings, and jogging bottoms), and a material with increased friction or grip properties could improve stability across these fabric types.

Another key issue highlighted by participants was the difficulty level of tasks assigned by the mobile application. Most expressed a preference for either a greater number of tasks or tasks of increased difficulty (e.g. 5000 steps rather than 100 steps). Although participants completed an initial profile questionnaire intended to personalise goal difficulty, the app currently distributes goals from a predefined database (Section 6.4.2), which limited the maximum difficulty achievable. To address this in future iterations, a more flexible, adaptive goal-setting algorithm could be developed, allowing personalised adjustments based on ongoing user performance, feedback, and progress, thus improving user satisfaction and long-term engagement.

7.6. Chapter Summary

Overall, the DAIM was found to be acceptable for home use by end-users and successfully met the design criteria, with several areas for further improvement identified. These include enhancing accessibility for upper-limb movements, refining the final intensity tracker by improving material grip, and reducing the size of both components and the battery. All participants indicated that they would use the device long-term in real-world settings as part of their rehabilitation journey. Regarding the community-based features, one participant appreciated the collaborative feedback aspect, another expressed indifference towards both competitive and collaborative elements, while the third preferred a more competitive approach to rehabilitation support. Further elaboration on these points, along with detailed recommendations for subsequent research and practical implications, will be discussed extensively in Chapter 8.

Chapter 8. Discussion

8.1. Overview of Chapter

This concluding chapter presents a critical discussion of the DAIM system development and evaluation, drawing on the co-design process, technical development phases, and final user evaluation to assess the project's success in meeting its original aims. This chapter will compare outcomes against published literature, highlighting limitations and making suggestions for the future development of the DAIM. This chapter therefore maps to the 'Evaluation' phase of the MRC framework (Chapter 3).

8.2. Key Outcomes

This thesis presents the design and user testing of a novel rehabilitation dosage and intensity tracking system suitable for implementation across clinical, research, and home-based settings. The development of this system was achieved through a rigorous, co- design process, involving iterative prototyping and continual refinement based on sustained stakeholder participation and co-design. The foundations of this process were informed by the core design requirements identified by the stakeholder focus groups detailed in Chapter 3 and summarised in Table 7. These key requirements were identified as:

- Continuous rehabilitation
- Rehabilitation tracking
- Peer communication

Each of these elements were actively incorporated into the design, development, and testing of the DAIM system. The process was undertaken with a view to supporting ongoing refinement and scalability, with the long-term aim of developing a robust, user-approved model suitable

for potential commercialisation. In recognition of this commercial potential, the system was also designed to be low-cost, portable, easily manufactured, and implementable across the range of rehabilitation settings.

8.2.1. The Design Process

Throughout this project, the DAIM underwent multiple iterative stages of prototype development, each guided by co-design principles and informed by participatory stakeholder feedback. These processes were aligned with the MRC framework for complex intervention development (Skivington et al., 2021), which outlines four key phases: Developing or Identifying a Complex Intervention, Feasibility, Evaluation, and Implementation (Chapter 3). It is important to note that these phases are not intended to be followed in a strict linear sequence. The framework acknowledges the inherent complexity of developing health interventions and encourages an iterative, flexible approach where earlier stages may be revisited in response to emerging findings or evolving design needs. This same principle is reflected in the structure of this thesis, where discussions of each phase may reference previous chapters or sub-sections out of chronological order to reflect the dynamic nature of the development process.

8.2.2. Developing or Identifying a Complex Intervention

The development of the DAIM system was informed by a literature review (Chapter 2) exploring current practices in measuring rehabilitation dosage and intensity, and the use of wearable technologies for this purpose. The review revealed a lack of clear definitions and standardisation around terms like “adherence,” “dosage,” and “intensity,” which are often used interchangeably (Goikoetxea-Sotelo & van Hedel, 2023; Lang et al., 2009; Stinear et al., 2020). This conceptual ambiguity hinders effective tracking of patient rehabilitation progress and impedes research on optimal stroke rehabilitation dosage.

This gap is evident in the UK SSNAP database, where rehabilitation data is recorded manually at the discretion of AHPs, resulting in inconsistent and incomplete records (Gittins et al., 2020). The challenge worsens once patients transition to self-managed home rehabilitation, where adherence declines sharply, 30–50% of stroke survivors stop prescribed exercises within a year (Kåringen et al., 2011; Morris & Williams, 2009). Despite the known variability in adherence behaviours, no gold standard for measuring it exists, largely due to the blurred boundaries between adherence and dosage (Holden et al., 2014).

In response, DAIM was developed as a wearable device with wireless data logging and a companion mobile app, providing an objective, continuous method of tracking stroke rehabilitation dosage and intensity across all care settings. This approach offers several key advantages:

- The use of telecommunication technologies, including mobile phones, Bluetooth, and NFC, supports remote delivery of daily rehabilitation goals and tracks dosage.
- The incorporation of sensors to objectively capture patients' exercise movements provides real-time objective feedback, informing a more tailored rehabilitation prescription.
- The mobile application's delivery of interactive features, including personalised exercise programmes, progress tracking, and community-based support tools, promote user engagement and adherence.

Current telerehabilitation efforts primarily focus on improving adherence but lack accurate tools to measure exercise performance itself (Stephenson et al., 2022). With growing interest in hybrid care models that integrate telerehabilitation with traditional in-person services (Knepley et al., 2021), DAIM was designed to function across all rehabilitation settings: clinic, research, and home.

This development followed guidance from the MRC Framework and the INDEX study (Cathain et al., 2019), which outlines steps for developing complex interventions. These were addressed through: a literature review (Chapter 2), co-design through stakeholder focus groups (Chapter 3), and ongoing iterative development in collaboration with stakeholders (Chapters 4, 5, and 7). While not every INDEX criterion can be fulfilled by all interventions, this project has addressed the majority, as detailed in Appendix 12.

8.2.3. Feasibility

Following the Development Phase, the DAIM prototype underwent multiple rounds of iterative testing in accordance with the MRC's Feasibility phase (Skivington et al., 2021). The primary aim of this phase is to assess whether the intervention and the methods used to evaluate it are both practical and acceptable, whilst also ensuring alignment with the design criteria established in Chapter 3.

The DAIM system was tested through a series of structured, small-scale and large-scale studies designed to reduce uncertainty surrounding the DAIM. Across Chapters 4, 5 and 7, feasibility testing was used to examine core parameters such as ease of data collection, user adherence, and the practical viability of real-world deployment. These studies provided insight into how the device performed in diverse environments and whether users could operate it independently. Chapter 4's dosage validation study tested whether data from the DAIM could reliably reflect rehabilitation activity when compared to clinician-recorded logs, helping reduce uncertainty around data accuracy and collection. A similar study in Chapter 4 also applied this to a research setting at a rehabilitative gym (TERG).

The device lifecycle also incorporated a form of evaluability assessment during the early stages of the project. As described in Chapter 3, design requirements were generated through the stakeholder collaboration and refined over multiple co-design iterations, resulting in a shared

understanding of the intervention's intended outcomes and context. These discussions, supported by focus group polling and thematic analysis, ensured that the system could be realistically tested and measured. The iterative prototype testing across the development cycle also demonstrated that the intervention was both deliverable and acceptable and thus fulfilled the core criteria of evaluability prior to progressing to broader implementation considerations.

While a formal economic evaluation was outside the scope of this project, the feasibility studies indirectly contributed to understanding cost-related factors. The use of off-the-shelf, low-cost electronics was deliberately chosen to ensure the system remained affordable and scalable. Insights from these studies, such as battery limitations, participant preferences, and clinician feedback, informed realistic projections about future usability and deployment costs. The positive outcomes across feasibility, validity, and acceptability metrics, coupled with the scalability potential discussed in Chapter 8, support the likelihood that further investment in a full-scale evaluation would be worthwhile.

8.2.4. Evaluation

The evaluation phase was a critical part of this thesis, generating the evidence needed to assess the DAIM system's performance, feasibility, and alignment with clinical and user-centred goals. Following the MRC Framework, the evaluation extends beyond effectiveness to include usability, acceptability, contextual fit, and potential for meaningful behavioural change.

This chapter reflects that broader evaluation scope, integrating both quantitative performance metrics and qualitative user insights to assess how well the DAIM system meets clinical and user-centred goals.

When summarising the key performance metrics of the DAIM system components (Table 53), exceeded established benchmarks for usability, acceptability, and validity. The system achieved a mean SUS score of 83.33, surpassing the commonly accepted threshold of 68,

indicating strong overall usability (Hyzy et al., 2022). Additionally, the IMI score of 5.88 and the excellent ratings across most UEQ subscales further demonstrate high levels of user engagement and satisfaction. Specifically, the dosage component achieved a SUS score of 91.43 and an IMI score of 6.29, both comfortably exceeding benchmark thresholds, alongside a digital-to-manual time difference well within the acceptable ±5% range. The intensity tracker component demonstrated strong validity with 96% step count accuracy and over 94% accuracy in cycle repetitions and cadence. While step cadence accuracy (89.7%) narrowly missed the 90% benchmark, this minor shortfall is addressed in section 8.5.1, with targeted recommendations for improvement outlined in section 8.8. Overall, these findings validate that the DAIM system was developed successfully and is suitable for implementation.

Table 53 Key Metrics of DAIM System Components Compared to Established Benchmarks

Component	Metric	Result	Benchmark Criteria
Entire System	SUS	83.33/100	SUS benchmark score ≥68 indicates good usability (Hyzy et al., 2022).
	IMI	5.88/7	IMI score above 4.5 indicates successful motivation (Moscoso et al., 2025).
	UEQ	Majority subscales excellent	Excellence criteria for UEQ subscales (Schrepp et al., 2017).
Dosage	SUS	91.43/100	SUS benchmark ≥68 (Hyzy et al., 2022).
	IMI	6.29/7	IMI benchmark ≥4.5 (Moscoso et al., 2025).
	Digital vs Manual Agreement	Mean difference: 1.23 minutes	Acceptable difference ±5% (Zanier et al., 2007).
Intensity	Accuracy (Step Count & Cadence)	96% steps, 89.7% cadence	Accuracy benchmark ~90% (Thorup et al., 2017; Tophøj et al., 2018).
	Accuracy (Cycle Reps & Cadence)	96% reps, 94% cadence	Accuracy benchmark ~90% (Thorup et al., 2017; Tophøj et al., 2018).
	User Operation Capability	100% independently operated	Task success rates of 93% would be acceptable (Devittori et al., 2024)

The DAIM was not evaluated solely in terms of its usability scores or its ability to track dosage and intensity, but also in terms of how it supported user engagement, aligned with rehabilitation goals, and integrated into different contexts (home, research, and clinical settings). Chapter 7 included a mixed-methods acceptability study that captured not only user performance data (e.g. step counts, repetitions, cadence) but also rich qualitative feedback on how participants used the device, what it meant to them, and how it impacted their motivation and rehabilitation behaviour.

A key part of this evaluation involved comparing the final DAIM prototype against the original design requirements set by stakeholders during the early co-design process (Chapter 3). Table 54 maps these requirements against the features developed and implemented. The system successfully met all high-priority criteria, including daily goal setting, group tracking via the "team streak" function, and real-time logging of rehabilitation movements. Medium and low priority features, such as broader family support and clinician-facing dashboards, were only partially addressed in this version and present opportunities for future enhancement.

Table 54 Alignment of the DAIM system with original design criteria

Original Design Requirement	Description	Priority	How the DAIM system meets this requirement
Self-rehabilitation advice and rehabilitation motivation	The intervention should provide clear and effective self-rehabilitation indicators for users to prevent them from feeling directionless and dissatisfied.	High	The mobile application sets daily rehabilitation goals based on responses to an initial user profile survey, offering personalised guidance and promoting adherence.
Communication and support	The intervention should promote effective communication and support between healthcare professionals and users to ensure a smooth transition from rehabilitation to self-rehabilitation.	Low	The feasibility and validity study explored the potential for clinical use of rehabilitation dosage tracking to inform professional support.

Ongoing rehabilitation	The intervention should facilitate ongoing rehabilitation for chronic stroke patients and provide the necessary tools and strategies to manage their recovery journey.	High	Daily rehabilitation goals and a group-based "team streak" feature in the app encourage ongoing engagement and structured progression.
Peer support	The intervention should foster peer support and social connectivity among users to promote motivation and provide valuable support.	High	The "team streak" tracker allows users to monitor group and personal progress.
Family and friend support	The intervention should provide supplementary self-rehabilitation options that can provide social connectivity in the absence of family support.	Medium	Group goal tracking enables social connection and motivation between peers, even without direct involvement from family or friends.
Movement tracking sensor	The intervention should include a movement-tracking sensor to track rehabilitation progress and provide visual feedback.	High	The wearable thigh tracker captures step counts, cycling repetitions, cadence, and sit-to-stand transitions. The dosage tracker logs both the frequency and duration of rehabilitation activity.
Mobile application	The intervention should include a mobile application that enables stroke patients to track their rehabilitation progress, interact with a community, and access various features that promote motivation.	High	The DAIM app provides daily rehabilitation goals, a logging system for custom exercises, and a team goal tracker.
Group tracking feature	The mobile application should include a group tracking feature that enables stroke patients to track their self-rehabilitation progress as a group, providing overall visual feedback to promote motivation.	High	The group “team streak” feature provides visual feedback on collective rehabilitation activity; the personal goals page also offers visual feedback on the completion of activities.
Design for ease of use and accessibility for individuals with disabilities	The intervention useability and accessibility should be optimised for individuals with disabilities	Medium	Usability testing was conducted across iterative development cycles.

The DAIM system was developed as a low-cost solution for supporting stroke rehabilitation, with the total material expenditure across all components amounting to £145.68. It is important to note that, for the purposes of this project, all components were commercially sourced in small quantities and assembled manually, with labour costs contributing significantly to the total estimated cost (£5494.50). These figures are not, however, reflective of the cost structure that would be associated with large-scale manufacturing. In a production setting, unit costs would be substantially reduced through bulk purchasing of electronic components, which typically attract significant volume discounts. Additionally, certain commercial components currently used such as the Arduinos' and LCDs, could be replaced with custom-manufactured alternatives that eliminate redundant features, and reduce overall part count. The extensive man-hours required during the prototype phase (for design iteration, hand assembly, and troubleshooting) can also be eliminated altogether through streamlined manufacturing processes. Therefore, the DAIM system demonstrates strong potential for cost-efficiency and scalability when considering its implementation into real-world settings.

Table 55 Cost breakdown of the complete DAIM system, including hardware components and estimated labour at UK minimum wage (£12.21/hour)

Component	Description	Material Cost	Man-Hour Cost
1. Intensity Tracker			
Iliotibial band compression wrap	Fabric-based support band	£13.99	–
Arduino Nano 33 IoT (with headers)	Microcontroller	£26.20	–
Power bank	Portable power supply	£19.99	–
Black felt fabric	20cm x 20cm portion of 1m² sheet	£0.40	–
Hollowfibre filling	5g of 500g pack	£0.08	–
Dupont wires	4 wires out of 120 pcs	£0.20	–
RGB 16x2 LCD Display (I2C)	Visual interface	£14.00	–
Labour	Assembly and testing ~100 hrs	–	£1221.00
Subtotal – Intensity Tracker		**£74.86**	**£1221.00**

2. Dosage Tracker			
3D printed plastic box	1 unit from set of 5	£22.00	–
Arduino Nano 33 IoT	Microcontroller	£26.20	–
Mini oval speaker	Audio component	£2.20	–
LEDs	2 out of 500 pcs	£0.03	–
Power bank	Portable power supply	£19.99	–
Dupont wires	8 wires out of 120 pcs	£0.40	–
Labour	Assembly and testing ~150 hrs	–	£1831.50
Subtotal – Dosage Tracker		**£70.82**	**£1831.50**
3. Mobile Application			
App (built in Android Studio)	No licensing costs	£0.00	–
Labour	Design and development (~200 hrs @ £12.21/hr)	–	£2442.00
Subtotal – Mobile App		**£0.00**	**£2442.00**
Total Project Cost		**£145.68**	**£5494.50**

8.2.5. Implementation

The final phase of the MRC Framework, Implementation, focuses on promoting adoption and sustainability of an intervention in real-world settings. Although considered the final step, implementation was embedded throughout the DAIM project (Section 8.2.2) and evaluated explicitly in the acceptability (Chapter 7) and feasibility/validity studies (Chapter 5).

To maximise real-world adoption, early consideration was given to stakeholder needs through focus groups with allied health professionals (AHPs) and iterative feedback loops at each development stage. As a result, DAIM emerged as a wearable device capable of tracking rehabilitation dosage and intensity, initially designed for stroke but with applicability to other conditions such as spinal cord injury.

Implementation readiness was further supported by the repeated use of usability (SUS) surveys (Chapters 4, 5, & 7), which helped to align development with stakeholder needs and maintained a clear focus on implementation from the outset. Conducting an acceptability study in end-

users' homes also allowed the collection of rich and valid data that reflected authentic usage scenarios but importantly showed that the technology was adoptable in home-settings in both aphasic and non-aphasic groups. Additionally, the longevity and success of the dosage validation study in the clinical setting also demonstrated the DAIM's very high potential for AHP adoption.

Scalability and affordability were core design goals. The device was made portable, low-cost, and easy to set up, addressing common NHS adoption barriers such as perceived complexity and staff hesitance (Kerr et al., 2018). Stroke severity and clinician perceptions have also been shown to influence technology acceptance, making usability and clarity vital (Broderick et al., 2023).

While the man-hours associated with prototype development were significant (Table 55), the actual production cost of the device was kept relatively low as the device does not require particularly expensive components and instead relies on components and software which is readily available to the general public. Cost remains a critical issue in both clinical and home contexts, often tied to perceived complexity, integration effort, and unclear benefits (Agbemanyole et al., 2024). Moreover, usability and cost are frequently interlinked as if a device is perceived as complex or its benefits are not immediately apparent, both clinicians and end-users may be reluctant to engage with it (Mitchell et al., 2023). The high useability results from both AHPs and those with stroke combined with previous results reaffirmed that the DAIM could be implemented in the environments it was designed for and had the potential for further scalability.

8.2.6. Reflecting on Co-design

8.2.6.1. Choice of the Co-design Methodology

As previously mentioned in Chapter 3, the decision to adopt a co-design approach for developing the DAIM system was influenced by the substantial evidence highlighting poor adoption rates of rehabilitation technologies that fail to involve end-users meaningfully in the design process (Kerr et al., 2024; Mitchell et al., 2023; Sweeney et al., 2020). Co-design methodologies address this limitation by actively engaging stakeholders throughout each stage of development via structured focus groups, iterative design requirement generation, real-world testing, and comprehensive follow-up (Celian & Rafferty, 2022). Recent literature consistently advocates for such transdisciplinary stakeholder engagement, emphasising its role in identifying practical usability concerns and generating actionable feedback that directly informs iterative design improvements (Clanchy et al., 2024). Additionally, involving end-users fosters a sense of trust, ownership, and empowerment among participants, as they directly witness their input influencing the technology being developed (Mitchell et al., 2023).

Many rehabilitation technology studies predominantly emphasise quantitative metrics, such as performance scores, adherence rates, or clinical outcomes, while often underutilising qualitative feedback mechanisms that capture user experiences and perceptions. Standardised tools like the SUS, IMI and UEQ are designed to assess usability, motivation, and user satisfaction. These instruments are not consistently employed in rehabilitation research in parallel to publications of qualitative data. For instance, a scoping review of lower limb rehabilitation systems highlighted a lack of systematic guidelines for selecting validation questionnaires, despite the availability of various instruments to evaluate user perceptions and experiences (Moscoso et al., 2025). This is also seen with focus groups or participant interviews where researchers would benefit from insight into the users' lived experiences,

challenges, and needs and how this may affect the users understanding and implementation of a device (Ohman, 2005).

Focus groups were specifically chosen to kick-off the co-design framework (Chapter 3) as they provide an interactive forum in which diverse perspectives and experiences can be openly shared. Despite known limitations like researcher influence or participant dominance (see Section 8.3.2), focus groups effectively allowed participants including aphasic stroke survivors to contribute actively to generating design requirements and priority features. Conducting these groups entirely online also enhanced accessibility, reduced participant burden, and enabled greater inclusivity, particularly benefiting aphasic individuals who might otherwise face barriers in traditional face-to-face sessions. The decision to adopt an online approach was based off the recent calls in literature for a hybrid-model of co-design (Anemaat et al., 2021).

Another key strength was the inclusion of real-world clinical and research testing (Chapters 4 and 7). Many rehabilitation technology studies primarily utilise controlled laboratory settings, limiting generalisability and relevance to real-world scenarios. The DAIM studies were deliberately structured to evaluate the prototype in authentic rehabilitation contexts, providing realistic data on feasibility, acceptability, and validity. These real-world evaluations were instrumental in ensuring the DAIM could be practically adopted and sustained within clinical, research, and home rehabilitation environments.

Overall, the development of the DAIM benefited from an enhanced approach that integrated both qualitative and quantitative approaches throughout each stage of component development and final testing. By embedding this mixed-methods strategy into the design process, the final study concluded that, within a relatively short development cycle of 2.5 years, the DAIM achieved high levels of usability and acceptability among end-users, supported by pre-validated components. Although the final testing phase did elicit some feedback and

suggestions for improvement, these were largely refinements rather than fundamental changes. Crucially, the DAIM met all stakeholder-defined requirements outlined in Chapter 3, and the additional recommendations served to strengthen the system rather than introduce entirely new requirements.

8.2.6.2. Alignment with the MRC Framework

The MRC framework for developing and evaluating complex interventions guided this thesis throughout each developmental phase (see Chapters 2 and 3, see Section: 8.2.2). According to the MRC, interventions should undergo systematic preliminary evaluations, including feasibility, validity, and acceptability studies, before progressing to large-scale implementation and effectiveness trials. As shown in Table 56, each DAIM component was systematically evaluated through dedicated studies addressing these criteria. The iterative and systematic evaluations conducted throughout the thesis confirm that the DAIM system met key feasibility, acceptability, and validity benchmarks, satisfying MRC guidance and providing a robust foundation for the subsequent implementation phase.

Table 56 Mapping of Thesis Chapters and Publications (posters, conferences and journals) to the DAIM Development Criteria and MRC Framework Phases

DAIM System Component	**Qualitative Study**	**Acceptability**	**Validity**	**Feasibility**
MRC Framework Phase	**Develop Intervention**	**Feasibility & Implementation**	**Evaluation**	**Feasibility & Implementation**
Dosage	Chapter 3	Chapter 7	Chapter 4	Chapter 4
Publication	“The codesign of a community self-rehabilitative intervention to support stroke		"A Co-designed Digital Device for Tracking Rehabilitation Dosage After Stroke: Validity and Feasibility Study in	"A Co-designed Digital Device for Tracking Rehabilitation Dosage After Stroke: Validity and Feasibility Study in a

	rehabilitation: A focus group”		a Clinical Environment"	Clinical Environment"
Intensity	Chapter 3	Chapter 7	Chapter 5	Chapter 5
Publication	“The codesign of a community self-rehabilitative intervention to support stroke rehabilitation: A focus group”		"Feasibility and Agreement of a Wearable Intensity Tracker for Lower-Limb Stroke Rehabilitation"	"Novel Wearable Intensity Tracker for Stroke Rehabilitation: Feasibility Study"
Mobile Application	Chapter 3	Chapter 7	Chapter 6	Chapter 6
Publication	“The codesign of a community self-rehabilitative intervention to support stroke rehabilitation: A focus group”			

8.2.6.3. Extent of Stakeholder Involvement Compared to Current Literature

The DAIM system's development was strengthened by the extensive involvement of over 60 individuals, including clinicians, academics, and stroke survivors, who collectively contributed more than 500 hours of testing and feedback (Table 57). When comparing this stakeholder involvement to current co-design studies in stroke rehabilitation technology (Table 58), it is evident that DAIM meets or exceeds common benchmarks. While typical co-design studies

range widely in participant numbers and total engagement hours, from approximately 20 participants and 24 hours (Said et al., 2024) to larger studies involving around 100 participants and up to 2,900 hours (Kerr et al., 2024), the DAIM reflects a substantial and robust co-design process, placing the research in alignment with recognised best practices.

Table 57 Total number of individuals involved in DAIM system development and testing, along with total hours spent using or contributing to the system design.

Study	Clinicians and Academics (n)	Total Hours	Stroke Participants (n)	Total Hours
Initial focus groups (Chapter 3)	2	2	6	12
Pilot study – Feasibility and accuracy of Arduino-based NFC loggers (Chapter 4)	5	5	-	-
Feasibility and effectiveness evaluation – Sir Jules Thorn site (Chapter 4)	2	25	9	144
Feasibility and effectiveness evaluation – Wishaw Hospital site (Chapter 4)	6	300	21	189
Intensity Tracker validation (Chapter 5)	2	13	13	13
Final acceptability study (Chapter 7)	-	-	3	12

Total	**17**	**345 hours**	**52**	**370 hours**

Table 58 Examples of participant numbers and total collective hours contributed during co-design processes in stroke rehabilitation technology development.

Study (Year)	Stakeholders Involved	Participant Count	Co-Design Engagement
Co-design of a walking activity intervention for stroke survivors (Wittink et al., 2024)	Therapists; (Patient & caregiver input via personas)	up to 15 per session	3 sessions × 4 hrs per person ~ 180 hours
A Participatory Model for Cocreating Accessible Rehabilitation Technology for Stroke Survivors: User-Centered Design Approach *(Kerr et al., 2024)*	Stroke survivors (chronic)	100 (92 completed programme)	8-week programme: ≥16 sessions ×2 hrs (≥32 hrs per person) > 2900 hrs
Co-designing resources for rehabilitation via telehealth for people with moderate to severe disability post stroke (Said et al., 2024)	Clinicians, Stroke survivors, Caregivers	21 (multistakeholder)	9 workshops ×2 hrs per person, 6 interviews ×1 hr per person ~ 24 hrs
Using experience-based co-design to develop mobile/tablet applications to support a person-centred and empowering stroke rehabilitation (Marwaa et al., 2023)	Stroke Survivors, Family, OTs/PTs, Patient-org rep, Developers, Researchers	40 (interviews) 25 (workshop 1) 7 (co-design meetings) 19 (workshop 2)	2 workshops ×2 hrs per person, plus interviews and meetings ×1 hr per person ~ 135 hrs
Development of a behaviour change intervention for improving physical activity amongst stroke survivors with physical disabilities: a co-design approach (Kwah et al., 2024)	Stroke survivors, Caregivers, Clinicians	17 (survivors and caregivers in workshops) 19 (survivors for interviews) 8 (clinicians for refinement meetings)	Interviews ×1 hr per person 2 co-design workshops ×2 hrs per person with follow-up clinician meetings ×1 hr per person ~ 61 hrs

8.2.6.4. Considerations and Alternative Methods

In terms of product design, several alternative development methodologies could have been adopted for this thesis. Common alternatives to the MRC framework include Agile, Lean, Waterfall, Stage-Gate, and Design Thinking. Although not originally created specifically for healthcare or rehabilitation settings, each methodology has demonstrated applicability in healthcare technology projects, and all generally follow a structured approach progressing from ideation through to deployment (Arandia et al., 2023; Meghna et al., 2024; Silva et al., 2013; Zhao et al., 2023). Agile and Lean methodologies emphasise rapid, iterative prototyping coupled with continuous user feedback, making them effective at quickly adapting to evolving requirements. In contrast, Waterfall and Stage-Gate approaches rely on sequential, well-defined stages with rigorous validation checkpoints, suitable for projects with stable and clearly outlined requirements. Design Thinking, typically represented through the "double diamond" model, alternates between expansive exploration of user needs and focused refinement of solutions, prioritising iterative, user-driven innovation.

Each of these methodologies has advantages and limitations when applied to stroke rehabilitation technology development (Table 59). Nevertheless, the decision to use the MRC framework for this project was justified by its structured approach explicitly designed to develop, evaluate, and implement complex healthcare interventions within clinical and research settings. The MRC's clearly defined phases facilitated rigorous academic validation while still accommodating meaningful, iterative user engagement through co-design. This resulted in the DAIM's successful intensive co-design approach which demonstrated that following the MRC framework's guidelines was an effective and appropriate method which exemplified the importance of meaningful, user-centred engagement in developing effective, practical, and acceptable rehabilitation technologies.

Table 59 Comparison of Development Methodologies for Stroke Rehabilitation Technologies

Methodology	Pros	Cons
Agile (Arandia et al., 2023; Meghna et al., 2024)	• Highly iterative with short sprints for rapid progress • Continuous user feedback • Adapts quickly to change	• Can be hard to plan long-term • Less recognized evidence generation
Lean **(Arandia et al., 2023; Silva et al., 2013)**	• Emphasises real-world feedback • Efficient learning with minimal waste • Fast to discard poor ideas	• Can underemphasise rigorous testing • Less structured process • Risk of user fatigue from repeated trials
Waterfall (Arandia et al., 2023)	• Clear, linear stages with well-defined outputs • Good for hardware or systems with fixed requirements	• Poor fit for dynamic user needs or iterative design • Late user testing may reveal flaws too late • Unsuitable for evolving rehab goals or customisation
Stage-Gate (Arandia et al., 2023)	• Allows systematic risk management for hardware-to-software integration • Ensures each development stage is properly validated before advancing	• Slower than Agile or Lean • User engagement limited to specific stages
Design Thinking (Arandia et al., 2023; Zhao et al., 2023)	• Strong user-centred approach • Iterative prototyping and testing	• May struggle to deliver clinical evidence unless paired with more formal frameworks • Can require extensive user time and facilitation skills
MRC Framework (Skivington et al., 2021)	• Evidence-driven with clear phases • Ideal for academic and clinical validation	• Less flexible to mid-development changes

8.3. Limitations

8.3.1. Technology & Design Limitations

The primary technology-related limitations arose from the fact that the lead researcher also served as the main developer, working under strict time constraints and with limited prior

experience in product design. As a result, early development focused on producing a minimum viable prototype (MVP) that could meet core functional requirements and generate user feedback, rather than on optimising aesthetics, durability, or manufacturing readiness. This "lean startup" strategy is common in early-stage medical device development, where it enables rapid assumption testing, cost reduction, and iteration based on real-world use rather than speculation (Arandia et al., 2023). Rapid prototyping, especially for novice designers, is recognised as a practical way to identify usability issues and refine device ergonomics before investing in high-fidelity versions (Deininger et al., 2017). While this approach led to a bulkier first-generation intensity tracking band and limited interface polish, it aligned with user-centred design principles that prioritise early feedback from stakeholders (Segall et al., 2024).

Another design limitation involved the physical robustness of the prototype, particularly the thigh-mounted dosage tracker. During the intensity trackers feasibility study (Section 5.4), two participants experienced disconnections between the rechargeable battery and the Arduino Nano 33 IoT due to excessive thigh movement. This led to power interruptions and halted data collection. Although the tracker was programmed to store the most recent data point and resume logging upon reconnection, these interruptions compromised the continuity of gait data and could influence participant behaviour. Users may have consciously adjusted their movements to prevent further detachment, potentially reducing the naturalness and intensity of rehabilitation exercises.

Rather than using a bulky 9 V rechargeable pack, the DAIM prototype could have employed a lithium-polymer (Li-Po) pouch cell, which offers lightweight, flexible form factors and superior energy density, making it well suited to wearable devices.

Several telerehabilitation studies featuring wearable devices have successfully employed lithium-polymer (Li-Po) batteries due to their favourable energy density, compact size, and

lightweight design (Garcia et al., 2022; Yassin et al., 2021). Such batteries however, require dedicated charging circuitry and entail safety concerns and unfamiliarity for a solo developer under tight timelines. Alternative ambient energy–harvesting approaches, such as triboelectric, piezoelectric, modular solar, or thermoelectric generators, show promise in supplementing power or enabling semi-autonomous wearable systems (Yu et al., 2024). Yet their low power output and the complexity of integration (e.g. intermittent computing, storage, unpredictable energy yield) make them less feasible for continuous sensor operation in an early-stage prototype. Additionally, Li-Po come at higher cost (often in the order of tens of pounds per pack). For prototypes or devices that require only a singular cell, the rechargeable power bank works out more cost effective.

8.3.1.1. Choice of Sensor

Component selection was necessarily constrained by researcher familiarity and tight timelines, precluding systematic evaluation of alternatives such as Raspberry Pi, various Arduino boards, or TinyCircuits designed for optimal form factor, cost, and durability. During the clinical usability phase, the intensity tracker reliably detected powered-assisted movements but consistently underperformed when capturing shuffle gait patterns, such as during wheelchair-to-chair transfers or walking shuffling steps, leading to exclusion of that data (Section 4.4). This reflects broader evidence that wearable inertial sensors frequently under-detect steps or misclassify gait events in individuals with short-stride or shuffling gait, due to reduced vertical centre-of-gravity displacement and minimal step acceleration (Clay et al., 2019; Díaz et al., 2020; Ollenschläger et al., 2022; Sieminski et al., 1997). Although shuffling movements could be accurately measured using optical markers and cameras, the practicality and cost-effectiveness of such systems make them unsuitable for widespread use in home, research, and clinical settings. Thus, reliance on wearable sensor technology remains essential for maintaining portability, affordability, and scalability.

Other sensors, such as foot-mounted inertial measurement units (IMUs) or pressure insoles, could have offered more accurate detection of shuffling gait by capturing subtle foot dynamics closer to the point of ground contact. These options were, however, not pursued due to limitations in budget, device complexity and development time. While commercial gait systems using such sensors do exist, they typically require multiple units per limb and involve sophisticated calibration processes. Crucially, this level of complexity would have conflicted with the project's core design priorities, specifically, the need to keep the system portable, easy to set up, and usable by individuals post-stroke, many of whom may have cognitive, motor, or perceptual impairments (Section 3.4.3.1). Meeting these user requirements was prioritised over maximising sensor precision at the cost of usability.

Additionally, the prototype lacked heart rate monitoring, which limited the system's ability to gauge physiological effort during exercise. Although DAIM successfully captured duration, frequency, and repetitions of rehabilitation tasks, it lacked the ability to assess intensity in a physiological sense. Incorporating a heart-rate sensor would provide critical feedback on exercise difficulty, highlighting whether tasks were too easy or too strenuous, and could prompt real-time adjustments via the app. Such integration would not only improve safety and personalisation but also enhance user engagement.

While consumer-grade wrist-worn photoplethysmogram (PPG) sensors (like Fitbit or Apple Watch) offer convenience, their accuracy diminishes at higher intensities and their performance can vary significantly, especially in clinical populations with their accuracy ranging from ~80–95% compared to ECG, $p<.001$ (Kroll et al., 2016; Martín-Escudero et al., 2023). Given the early-stage prototype's developer-driven design and resource limitations, adding such a sensor was beyond the technical and regulatory capacity at the time.

8.3.1.2. Choice of Software

The DAIM prototype included a basic feedback system with primitive gamified elements, yet it did not deliver a sophisticated gaming experience primarily because Android Studio, while effective for standard app development, lacks the built-in capabilities for advanced interactive content such as real-time rendering, physics simulations, intuitive animations, or dynamic feedback loops. Conversely, specialised game engines like Unity or Unreal Engine offer these features, along with strong cross-platform integration, streamlined animation workflows, and rich graphical rendering, making them ideal for engaging serious game development in rehabilitation contexts.

Telerehabilitation research has demonstrated the feasibility and patient engagement benefits of serious games developed in Unity, including systems like RehaBot and custom-built VR applications shown to boost adherence and motivation (Nicola et al., 2017). Unity-based telerehabilitation platforms have also been linked to improved exercise compliance and user satisfaction (Rodrigues et al., 2025).

Thus, future iterations of the DAIM could significantly benefit from first developing gamified elements within Unity or Unreal Engine and then integrating these externally developed games into the existing DAIM Android app. This approach would leverage the strengths of specialised game engines, providing users with a more engaging, interactive, and motivating rehabilitation experience.

8.3.1.3. Researcher Bias

One key limitation of the co-design focus group study (Chapter 3) was the potential for researcher bias. The focus groups were all led by the researcher, creating the risk of unintentionally guiding discussions towards predetermined expectations or preferences for certain measurements or components. This could have subtly encouraged participants to

provide responses that aligned with perceived expectations, rather than expressing their genuine needs or lived experiences. Although the presence of a research physiotherapist in every session helped mediate this risk, and supported a more balanced discussion, the possibility of researcher bias influencing participant feedback cannot be entirely dismissed. It is acknowledged, however, that the research physiotherapist also ran the TERG sessions, and so the participants would have also known them, which may have further impacted the study.

While participant selection bias is a common concern, particularly the tendency for co-design focus groups to attract more motivated individuals with generally positive rehabilitation experiences (Carlstedt et al., 2022), the quotes and themes drawn from the focus group transcripts suggested a more diverse range of perspectives. Several participants expressed pessimistic attitudes about their rehabilitation journeys, including frustrations about a lack of signposting, feelings of being lost without prescribed exercises, and an absence of measurable proof of progress. Although these individuals were still motivated enough to engage with the co-design process, their negative experiences and candid grievances helped ensure that the DAIM design process addressed real-world barriers and emotional challenges.

Additionally, while each focus group included a research physiotherapist and caregiver, the inclusion of a broader range of stakeholders, such as managers, stroke foundations, government representatives, designers, developers, community members, and quality improvement experts could have enhanced the comprehensiveness and real-world applicability of the resulting design criteria. A recent scoping review found that only 25% of co-design studies included stakeholders beyond clinicians and patients, despite evidence suggesting that broader stakeholder engagement significantly enriches intervention relevance and effectiveness (Singh et al., 2024). Moreover, the same review highlighted that 82% of stroke intervention co-designs used traditional methods such as workshops, interviews, and focus groups to gather data, aligning with the methodological choices of Chapter 3.

Another challenge pertains to group dynamics, particularly given that half of the focus groups included aphasic participants. There is always a risk that certain individuals might dominate discussions, resulting in those with aphasia not being given enough time to give their thoughts, this can lead to a design criterion that does not reflect the full range of perspectives. Whilst this type of dominance was perceived, the risk was minimised by utilising anonymous Zoom polling during the sessions to ensure every participant could independently voice their opinions on key design decisions, thus promoting equitable representation of all participants' views.

8.3.1.4. Sample Bias

It worth noting that the participants who volunteered for all of the studies except the clinical study (Section 4.5), might already have been inherently motivated, given their proactive involvement in the TERG sessions, which required them to organise regular transportation and attend rehabilitation sessions alongside daily responsibilities. This introduces a potential positive selection bias, as stroke survivors frequently face significant barriers to adhering to rehabilitation activities, such as physical impairments, low exercise self-efficacy, depression, lack of caregiving support, limited emotional encouragement, insufficient exercise prescription, inadequate monitoring and feedback, and organisational policy constraints (Zhang et al., 2023). Supporting this, literature suggests that individuals with strong social support networks are more motivated to engage consistently in rehabilitation (Lee & Won, 2022). Additionally, a recent study on stroke rehabilitation noted that volunteer participants are often biased towards those already interested in rehabilitation research, making the outcomes less generalisable to the broader stroke survivor population (Carlstedt et al., 2022). Therefore, caution must be taken when interpreting the findings from this study. Such biases could be mitigated in future research by employing diversified recruitment strategies to attract a broader, more representative sample beyond a single participant pool (the TERG). Furthermore, incorporating formal measurement of participants' baseline motivation and clearly reporting

detailed participant characteristics would facilitate better interpretation and applicability of the results.

This limitation was less evident during the clinical feasibility study (Section 4.5), in which the DAIM device was tested with any participant deemed medically fit to engage, regardless of their prior familiarity with technology or rehabilitation tools.

The small sample size of the final study (Chapter 7) was primarily due to the project's time constraints, which led to a brief recruitment period limited to participants from the current TERG study (Kerr et al., 2023). Nine individuals were approached; six declined to take part, five immediately and one after reviewing the PIS. The five who declined initially cited concerns that, due to their upper-limb mobility issues, they would be unable to independently don the wearable thigh tracker, an essential component of the study. The sixth individual, after reviewing the PIS, declined as they felt unable to commit to the one-week duration required for participation and anticipated feeling overwhelmed. Although there were only three participants, each was able to use the DAIM device between three and five times over the course of the week. On two occasions, participants used it for an uninterrupted hour at the TERG gym, resulting in a collective minimum usage time of six hours. It is also important to note that the DAIM recorded only the total number of steps, cycling repetitions, and sit-to-stand movements completed per day.

8.4. Implications for Future Research

Accurate and objective measurement of rehabilitation dose and intensity, as enabled by the DAIM system, holds sizeable implications for future research. Current methods for measuring rehabilitation dose both clinically and in research often rely heavily on subjective reporting, such as therapist notes, self-report diaries, or participant recall, each of which introduces considerable potential for error and recall bias (Levy et al., 2019). Additionally, existing

measures of adherence to physical rehabilitation exercises lack a universally accepted gold standard, typically depending on self-developed questionnaires or participant-reported outcomes that frequently lack robust psychometric validation (Bollen et al., 2014; Hall et al., 2015; Holden et al., 2014). Replacing or complementing these traditional methods with reliable, objective sensor-based metrics provided by the DAIM could enhance the rigour and validity of rehabilitation research by providing consistent, accurate, and continuous measurement of both dosage and adherence (Levy et al., 2019).

Rehabilitation dose, encompassing therapy intensity, frequency, and duration, is widely recognised as a critical determinant of patient outcomes, yet is currently poorly and inconsistently reported in clinical studies. Evidence indicates that incomplete reporting severely limits the interpretability, reproducibility, and generalisation of research findings (Bakaa et al., 2021; Hansford et al., 2022). For example, a comprehensive overview of systematic reviews found that, on average, only 24% of items on the Consensus on Exercise Reporting Template (CERT) and 49% on the Template for Intervention Description and Replication (TIDieR) checklist were adequately reported (Hansford et al., 2022). DAIM addresses these critical reporting gaps by capturing precise, objective, and contextually rich rehabilitation data, thus enabling researchers to systematically explore dose-response relationships.

Utilising DAIM, future research can robustly address nuanced questions, such as determining the optimal dose of rehabilitation for various patient subgroups (e.g., acute versus chronic stroke patients) and personalising therapy intensity based on specific impairments and functional goals. DAIM's objective intensity monitoring capability could identify distinct "rehabilitation profiles" that predict patient responsiveness to specific interventions, clarifying critical thresholds of daily step counts or activity intensity linked to long-term functional outcomes. Additionally, the system could help isolate which specific components of intensity,

such as steps, repetitions, or cadence, most significantly influence improvements in lower limb function and overall mobility. Finally, the DAIM's detailed monitoring could highlight correlations between objectively measured therapy intensity and secondary outcomes, including patient confidence, self-efficacy, and quality of life, thereby advancing the evidence base for optimising rehabilitation strategies.

Developing the DAIM system through this intensive and iterative co-design process, wherein each component (dosage tracker, intensity tracker, and mobile app) underwent its own cycles of validation and refinement based on end-user feedback, provides a robust template for future rehabilitation technology development. This user-centred approach ensures not only that each individual system component is tailored to real-world user needs but also that integration between components effectively meets broader research and clinical expectations. Furthermore, applying this rigorous, participatory method to future research can improve the acceptability, usability, and clinical relevance of novel rehabilitation interventions from the outset. Research consistently demonstrates that engaging users in iterative design and validation cycles reduces the risk of misalignment between user needs and technological solutions, resulting in interventions that are more likely to be successfully implemented and sustained in clinical practice (Botero et al., 2020; Vandekerckhove et al., 2020). Consequently, adopting this structured co-design framework could significantly enhance the effectiveness and practicality of new technological interventions across diverse rehabilitation contexts, encouraging wider adoption and greater user adherence.

Importantly, this system also challenges the concept of “usual care” (Section 2.3.4.1)| as used in rehabilitation and physical therapy research. In practice, “standard care” is rarely quantified, making it effectively meaningless in a scientific context. Without objective data, it is impossible to determine what treatment was actually delivered, at what intensity, or for how

long. DAIM introduces a way to measure "standard care" with fidelity, offering a more accurate baseline against which new interventions can be compared.

8.5. Implications for Clinical Practice

The DAIM system, integrating wearable sensors, a smartphone app, and contextual logging, holds strong potential for supporting hybrid models of rehabilitation. The COVID-19 pandemic accelerated the adoption of telerehabilitation, with growing evidence favouring hybrid models that combine remote and in-person care (Ackerley et al., 2023; Duncan & Bernhardt, 2021). For example, a London fracture clinic reported a >50% reduction in footfall with no compromise in satisfaction or clinical outcomes using a hybrid model (Sharma et al., 2021). Hybrid delivery has also been positively received by both patients and clinicians, especially where travel and limited access to services are barriers (Ellis et al., 2022; Land et al., 2025).

DAIM supports this hybrid approach by enabling remote monitoring and blending clinic-based sessions with structured home rehabilitation. This can naturally transition into long-term rehabilitation management, with AHPs staying updated on progress with minimal direct intervention, offering a more flexible, patient-centred alternative to traditional, clinic-only models.

By providing objective, real-time data on activity intensity and adherence, DAIM can help clinicians personalise therapy plans and intervene early when engagement issues arise. The system's ability to log frequency and intensity, and to flag missed sessions or deviations from targets, supports more precise and responsive care. Policy reviews further highlight the promise of wearables in tracking rehabilitation adherence, particularly post-surgery (Narain & Lally, 2025).

Although DAIM was developed for stroke rehabilitation, its core features: dose tracking, real-time feedback, and digital engagement, are applicable to a range of conditions, including

orthopaedic recovery, multiple sclerosis, Parkinson's disease, and frailty in older adults. Successful implementation in clinical setting however, is not without challenges, particularly regarding scalability, integrating within existing clinical workflows, IT infrastructure and data privacy concerns (Gardner et al., 2023). These design considerations can be mitigated early through the co-design approach by considering the requirements of all stakeholders involved.

The DAIM system is designed to act as a digital bridge across the entire stroke recovery pathway, facilitating a seamless transition from clinical environments to independent community living. In the initial acute phase, DAIM can be integrated directly into inpatient rehabilitation areas. Users are introduced to the system during their first interactions with therapy, allowing the dosage component to be utilised immediately. By pairing the device with the patient's mobile phone early on, clinicians can capture a bigger picture of their inpatient rehabilitation in real-time. As patients progress toward the sub-acute phase and prepare for discharge, the system facilitates a hybrid model of care. At this juncture, the user begins wearing the wearable intensity tracker and the full mobile app. Under professional guidance, the users with their AHP collaborate to set personalised home goals via the initial user profile set-up. The user can thus familiarise themselves with the hardware and interface before leaving the clinical setting. Once home, where adherence would typically drop, the DAIM system provides the teamwork and peer support features to maintain long-term motivation and prevent any directionless feelings previously reported by user's post-discharge. Furthermore, integrating DAIM into community rehabilitation centres ensures that tracking remains continuous.

However, whilst the current findings of this thesis support the system's potential, limitations must be addressed to ensure its efficacy across the entire pathway. Namely, that further work is required to optimise the intensity tracker for acute users to pick up slower movements which the current DAIM model can't pick up. Additionally, whilst home-setting adoption was

positive, larger longitudinal studies are needed to validate whether DAIM can sustainedly improve functional outcomes in diverse, unsupervised community environments. Further research should also consider how the entire DAIM system will integrate seamlessly into clinical environments and question how the data from the DAIM can be sent to any digital infrastructure without risk of data breaches.

8.6. Recommendations for Future Research

This thesis has demonstrated that the DAIM system is acceptable and feasible across clinical, research, and home settings within the stroke rehabilitation pathway. Future development should continue the user-centred, iterative approach to transition the prototype into a market-ready product. Feedback from the final acceptability study (Chapter 7) should guide design refinements. Further evaluation, ideally comparing DAIM to standard care and competitor devices, will be essential to validate its clinical and practical value, aligned with the MRC's final 'implementation' phase.

Based on participant feedback from interviews and diaries in Chapter 7, the following design recommendations are proposed:

- Task Difficulty: Tasks were generally too easy, even at maximum intensity. Users showed capacity and motivation for more demanding exercises. The app should include:
    - A larger, tiered activity library validated by AHPs
    - Adaptive goal-setting algorithms to increase complexity as users improve
    - A real-time Settings page for users to adjust intensity, duration, and challenge level within safe AHP-set limits
- Streamline the Band: The wearable intensity trackers' band was seen as bulky due to the external power bank. Improvements include:

    - A custom, ultra-thin lithium polymer battery
    - Retaining Velcro for ease of use
    - Adding internal silicone gripper tape for better stability
    - A compression sleeve variant with integrated sensors
    - Miniaturising components with a custom PCB combining microcontroller, gyroscope, BLE, and charging, with real-time data routed to the app
- Expansion to Upper-limb Movements: Users requested upper limb rehabilitation tracking to become measurable. To accommodate this:
    - Create a second interchangeable band for upper or lower limb sessions
    - Calibrate firmware and processing for upper limb motions
    - Position the band on the dorsal forearm to capture key movements
    - Include an in-app calibration routine to ensure accurate setup

Drawing on evidence from later-stage rehabilitation technologies in the published literature, the following priority studies are also recommended:

- Randomised Controlled Trial (RCT): A multi-centre RCT with three groups:
    - Usual care + DAIM
    - Usual care only
    - Usual care + comparator wearable.
    - Primary outcomes: Fugl-Meyer score, 10-Metre Walk Test.
    - Secondary: DAIM-logged dose, adherence, QoL, cost-effectiveness.
- Long-Term Adherence and Recovery Study: A 6–12 month longitudinal study linking wearable data with functional outcomes (e.g., gait speed, lower limb Fugl-Meyer scores). Qualitative interviews would explore motivational patterns and support modelling of effective rehabilitation “doses.”

With the current prototype meeting core stakeholder requirements, development can now focus on these refinements without altering the underlying architecture. This foundation enables future evaluations while maintaining a co-design approach.

DAIM has been formally disclosed via the University of Strathclyde's technology transfer portal (TECH 2344) to support commercialisation and funding. It is also included in an upcoming trial for rehabilitation dosage tracking in spinal cord injury, further demonstrating its versatility.

Postgraduate research projects could further refine DAIM and explore broader questions, such as:

- How can continuous, objective adherence and intensity data from DAIM be fed into adaptive algorithms that automatically adjust daily targets to maximise motivation and progression?
- Does DAIM's instant performance feedback improve long-term adherence compared with traditional paper diaries or standard home-exercise leaflets?
- Is remotely monitored, wearable-driven hybrid rehabilitation as effective, or more effective, than conventional inpatient programmes, and what are the economic and logistical implications of scaling such models across NHS services?

Chapter 9. Conclusion

This project successfully delivered a portable, low-cost Dosage and Intensity Monitoring system (DAIM) for rehabilitation, demonstrating both technical viability and real-world usability. The system was developed using a novel hybrid approach that blended co-design and participatory design methods, engaging AHPs, researchers and people with stroke throughout all phases of development. This iterative process allowed user needs to shape both the technical architecture and the user experience, ensuring that the final system addressed practical requirements and real-world constraints.

Functionally, DAIM enables individuals to objectively monitor their rehabilitation progress across various settings, including clinical, research, and at home. The device accurately detects and records key movement patterns using on-board sensors, a custom state machine, and local data processing. A peak and trough detection algorithm, paired with motion filtering and cadence calculation, showed that even subtle rehabilitative motions are captured with an adequate amount of accuracy. Persistence mechanisms, such as flash memory storage and Bluetooth synchronisation, guarantee data continuity despite power loss or connection interruptions. These design elements collectively ensure reliable, accurate tracking of exercise dosage and intensity.

Real-time feedback, personalised goal-setting, and gamified progress indicators were integrated as per the co-design requirements to promote sustained user engagement and adherence to rehabilitation guidelines. In line with the 3-hour daily rehabilitation target, the system supports users in building long-term habits through immediate and encouraging feedback loops. Community app features app integration allows users and clinicians to monitor cumulative progress and make timely adjustments to rehabilitation plans.

Clinical and field testing validated the system's measurement accuracy, demonstrating close alignment with manual recording methods used by AHPs. These results confirm that DAIM is both technically robust and suitable for deployment in rehabilitation environments where measurement accuracy is paramount.

The final acceptability study, which captured user impressions after extended use, showed strong alignment between the system's actual performance and the co-designed expectations identified at the outset. Participants reported high levels of usability, clarity of feedback, and motivation to remain active. Importantly, users also recognised the value of the system in bridging gaps between clinical supervision and independent rehabilitation, particularly in underserved or remote settings.

While the system was initially tailored to stroke rehabilitation, its modular, sensor-agnostic architecture supports easy adaptation to a wider range of lower-limb rehabilitation contexts, including post-operative recovery, ageing-related mobility loss, and chronic disease management. The DAIM platform thus holds promise not only as a research tool but also as a scalable, deployable solution for real-world rehabilitation tracking.

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Appendix 1. Thematic Codes

Table 60 Initial Codes Collected from Focus Group

Initial code	n of participants contributing (n=6)	n of transcript excerpts assigned	Sample quote
The user felt that there was a lack of communication between their NHS healthcare professional and themselves during their time receiving stroke rehabilitation.	3	7	"I see my physio once a fortnight… that's just when I can get her. I've not seen my GP in 2 years" (P3)
The ending of their stroke rehabilitation programme was unclear.	3	3	"I was just told 'that's the end' when they went away" (P1)
The user felt that their NHS healthcare professional was not encouraging them or was quick to put them down.	3	3	"They keep saying that 'aw you're getting a wee bit better, but you'll never be any better than you are', and that I can't do better. Even if you do have an improvement, they sort of are very quick to knock you back down" (P3)
The user feels like they still require some consistent form of physical, cognitive or speech rehabilitation.	3	6	"My biggest deficit is still my left arm. I mean I've got no movement below my shoulder in my left arm at all." (P5)
The user is currently partaking in stroke self-rehabilitation.	4	4	"Well, I don't do anything. I'm basically self-managing as such" (P2)
Users use devices at home to help with daily stroke rehabilitation.	5	8	"I'm doing this now [shows to the camera the Home GRASP booklet]. That is absolutely superb… It's good for me" (P6)
Users believe that motivation is a key factor in their rehabilitation journey.	5	4	"You basically just have to keep trying… That's that the hardest thing that the hardest thing is to stay positive and stay on course." (P2)
The user is currently partaking in stroke self-rehabilitation.	4	10	"On Mondays I still go to the to that thing for getting in the water [referring to a hydropool], and then the next day. I got the 2 I just talked about [referring to two exercises at the gym], but that's enough. And then on Wednesday, whether it's outside in the rain, or back inside [referring to stroke support group]" (P1)
Users have actively sought out and received private physiotherapy to help with their stroke rehabilitation after hospital discharge.	2	9	"I mean I did get some (referring to physiotherapy) when I came out from hospital at first, but it tailed off very quickly, which is why we went for private physio." (P5)
Users have actively sought out or partake in charities or support groups to help with their stroke rehabilitation after hospital discharge.	2	2	"I mean, like once a week I have the support worker coming from Cornerstone, too." (P5)
Users have actively sought out and partake in experimental research to help with their stroke rehabilitation after hospital discharge.	6	6	"I was approached by when I was in Langlands by J.Alexander, and I got sable glove trial thing, so that was like 16 weeks, 15 or 16 weeks" (P2)
The user feels like their social needs are important when undergoing stroke self-rehabilitation or self-rehabilitation.	3	3	"Being part of something, that's the social aspect of your app. Any kind of interaction. It's really positive." (P2)
The user feels that the ability to be social is a key motivator in their stroke rehabilitation journey.	4	6	"I've found it hard to replace that afterwards. It kind of accelerated what I was doing. I think the repetitions and the immediacy of it, and also the group thing, working with other people" (P2)

The user feels supported when surrounded by other people who have experienced a stroke.	2	1	“Because I’m by myself, I'm bored sometimes. I need something else would be better for me” (P6)
The user would like to see more social options when undergoing self-rehabilitation.	5	3	“I would love that. That would be very good.” (P1)
Some users currently rely on family and friends to help them achieve self-rehabilitation and self-rehabilitation.	2	2	“But I get it from my friends. She comes in Monday, Tuesday and Wednesday, the rest I have got to do myself, but it's okay, better than nothing.” (P1)
Users felt that their rehabilitation journey was impacted by COVID-19.	1	1	“The problem is with the virus. We didn't do it. So those are problems, I had 2 years where I did nothing, and now I have to do it again.” (P6)
Users would like to observe their achievements and progression if they do not want to partake in community goal achieving.	2	2	“P4: I like to do one thing. Fiona Boyd: you like to do your own thing. So would you be happier than just looking at your own achievements and looking at your progression. P4: [Nods].” (P4)
Users feel that receiving encouraging feedback will promote motivation in completing their daily tasks.	5	3	“Yeah, I think the app might benefit from kind of group thing or somewhere where you can, you know, just clock in with other people, because it would be, you know, affirming, yeah. That’s very important.” (P2)
Users would like to communicate and support team members whilst completing daily tasks.	4	3	“No I’d probably do it to be honest” (P3)
Users experience personalised rehabilitation progression monitoring when receiving their NHS physiotherapy.	2	3	“When I’m working with my physio, we tend to so try and focus on things we want to achieve because it allows me to do things. So the moment we're just starting to do a wee bit walking without a stick as a goal, being able to go through to the kitchen, make myself a cup of coffee, and then walk bath with it, to my seat. It is functionality… It's quite personalised” (P5)
Users would like to see a form of personalisation whilst using the device.	2	7	“If you could make the app work like that” (P5)
Participants are satisfied in being able to access their progress should they require it	6	2	“I think it' be useful for it to be available, should you require. If you I mean as much as much, it's easy to say that you do something… You can't be refuted. If you've got this, nobody can say “oh you didn't do that… It’s probably worthwhile.” (P2)
Participants are satisfied with having a device that can be strapped around a wrist or a thigh.	2	1	“I think that'd be really good thing, and that, like anything that goes around the wrist like the leg thing that can the track movement and anything that can encourage that, even if it doesn't really do you know as much, the fact as you're trying to do, because you know, you’re trying to engage with it. It'd be good.” (P2)
Participants are satisfied using either their phone or tablet to access the app.	6	2	“Aye” (P3) “Yeah” (P1)
Participants found that their stroke does minimal impact on how they operate their phone or tablet and already have accommodations where assistance is required (i.e. using a tablet when the screen is too small on a phone).	4	2	“Yeah bigger screen” (P5) “I need it (referring to their tablet) because I have to use it all the time. So it's good. This one, the one I’m using just now is good. (P1)

Table 61 Grouping of initial Codes to form themes including where the identified themes will

Theme	Initial codes grouped to form theme	n of participants contributing (n=6)	n of transcript excerpts assigned	Addressed by Intervention
Support and quality of care after discharge	• The user felt that there was a lack of communication between their NHS healthcare professional and themselves during their time receiving stroke rehabilitation. • The user felt that the ending of their stroke rehabilitation programme was abrupt. • The user felt that their NHS healthcare professional was not encouraging them or was quick to put them down.	3	13	Application providing platform that users can input their self-rehabilitation plan (UX) Hardware providing accurate tracking of rehabilitation exercises (Hardware)
People actively are seeking sufficient rehabilitation for stroke post-discharge	• The user feels like they still require some consistent form of physical, cognitive or speech rehabilitation. • The user is currently partaking in stroke self-rehabilitation. • Users use devices at home to help obtain stroke rehabilitation. • Users believe that motivation is a key factor in their rehabilitation journey. • The user is currently partaking in stroke self-rehabilitation. • Users have actively sought out and received private physiotherapy to help with their stroke rehabilitation after hospital discharge. • Users have actively sought out and partake in charities or support groups to help with their stroke rehabilitation after hospital discharge. • Users have actively sought out and partake in experimental research to help with their stroke rehabilitation after hospital discharge.	6	47	Application providing motivation and tracking of user completing NHS recommended self-rehabilitation exercises for recommended duration (UX)
Social support as a motivator in self-rehabilitation	• The user feels like their social needs are not prioritised when undergoing stroke self-rehabilitation or self-rehabilitation • The user feels that the ability to be social is a key motivator in their stroke rehabilitation journey. • The user feels supported when surrounded by other people who have experienced a stroke. • The user would like to see more social options when undergoing self-rehabilitation.	5	13	Application based around social connectivity (UI)
Reliance on community support	• Some users currently rely on family and friends to help them achieve their self-rehabilitation and self-rehabilitation. • Users felt that their rehabilitation journey was impacted negatively by COVID-19 as they were unable to partake in community-based rehabilitation, access their support groups and could not see family or friends.	2	3	Application based around social connectivity (UI)
Co-design considerations I – UI	• Users would like to observe their achievements and progression if they do not	5	8	Application UI

	want to partake in community goal achieving. • Users feel that receiving encouraging feedback will promote motivation in completing their daily tasks. • Users feel that working together to achieve group daily goals is rewarding.			
Co-design considerations II - UX	• Users experience personalised rehabilitation progression monitoring when receiving their NHS physiotherapy. • Users would like to see a form of personalisation whilst using the device. • Participants are satisfied with being able to access their progress should they require it	6	12	Application UX
Co-design considerations III – Hardware	• Participants are satisfied with having a device that can be strapped around a wrist or a thigh. • Participants are satisfied using either their phone or tablet to access the app. • Participants found that their stroke does minimal impact on how they operate their phone or tablet and already have accommodations where assistance is required (i.e. using a tablet when the screen is too small on a phone).	6	5	Accompanying Hardware

Appendix 2. CAD Drawings

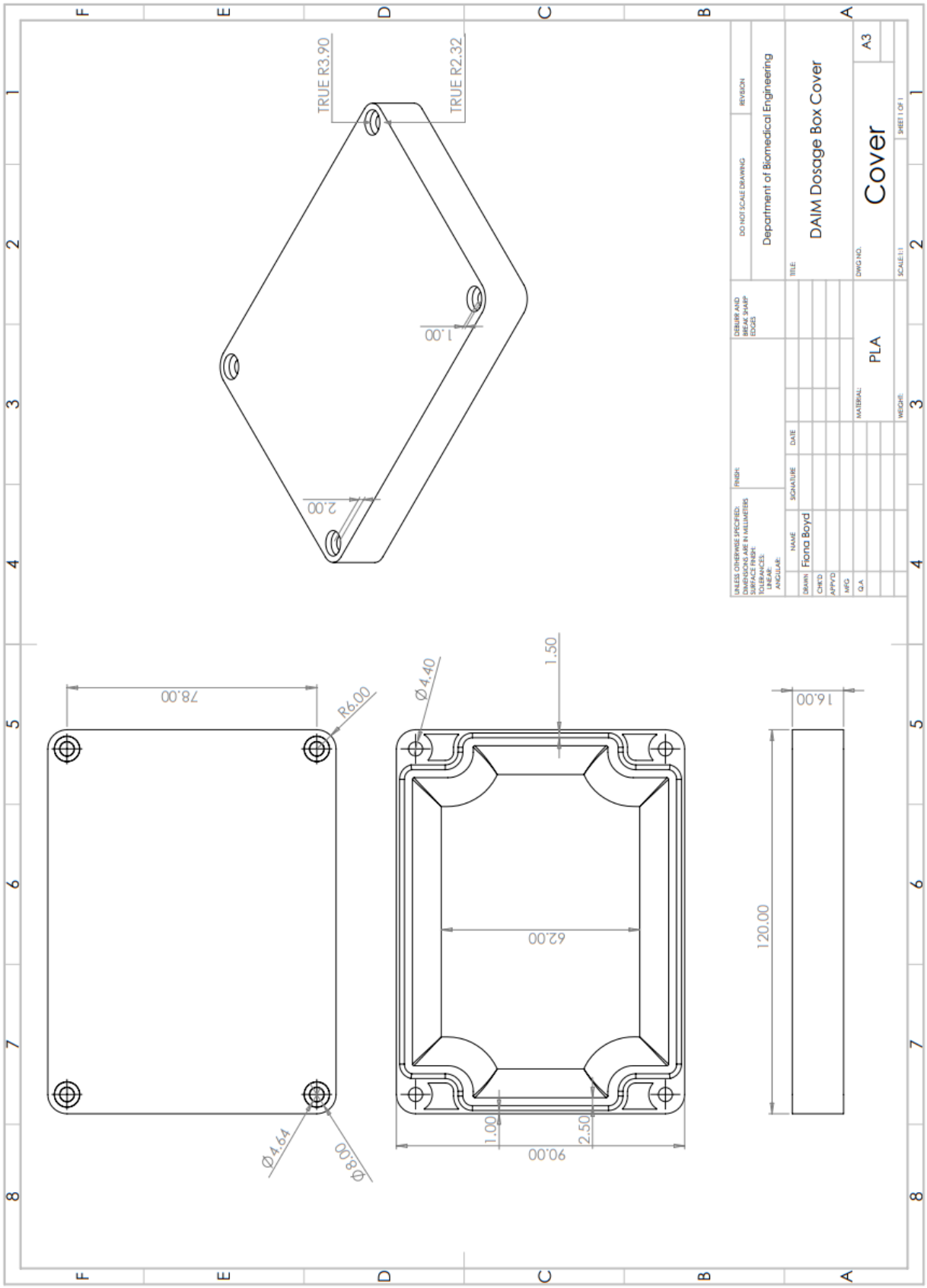

Figure 58 Solidworks CAD drawing of dosage component cover

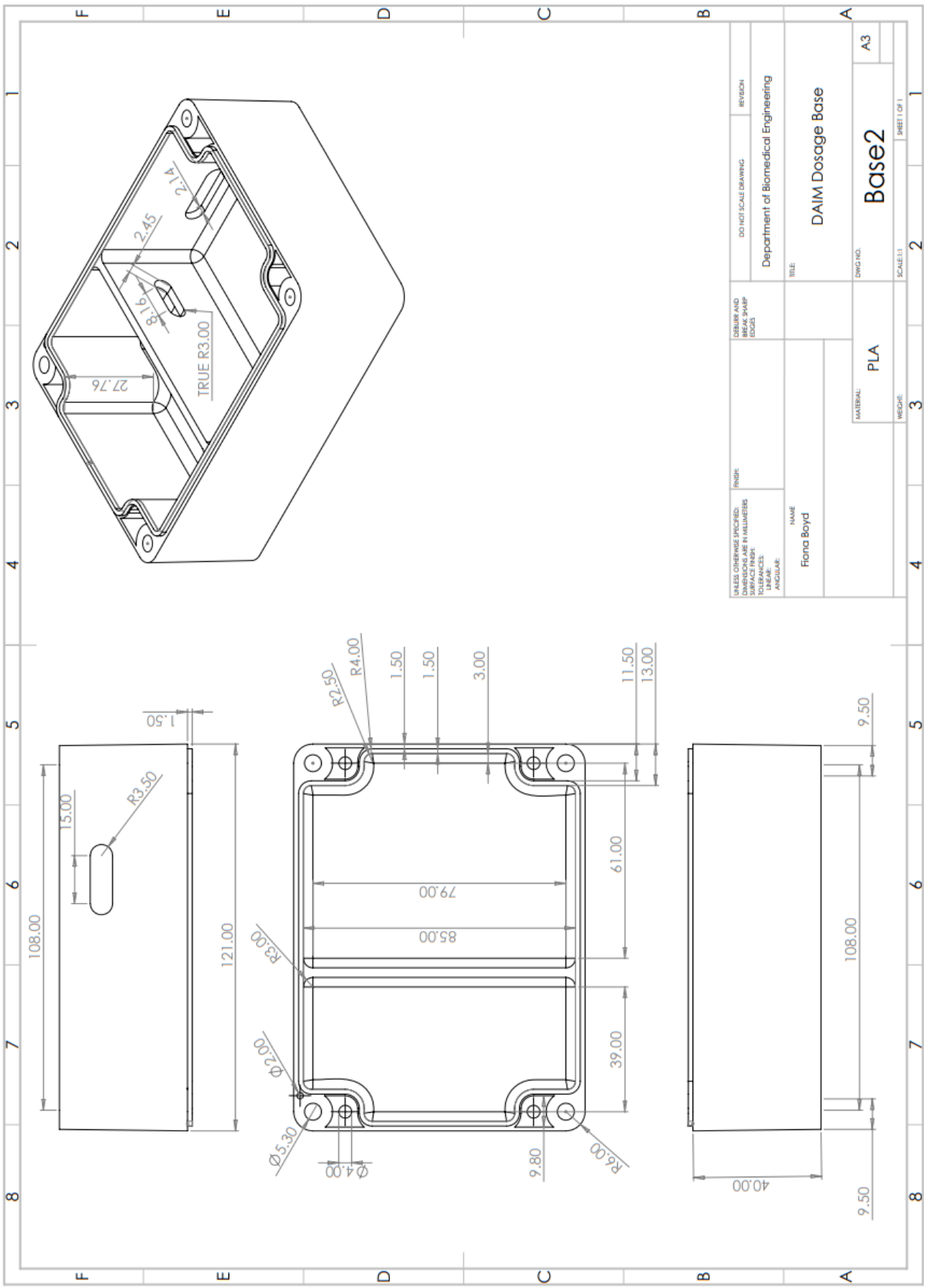

Figure 59 Solidworks CAD drawing of dosage component base.

Appendix 3. Dosage tracker Arduino Nano 33 IoT Coding

Double click script to open in new page.

```
#include <FlashAsEEPROM.h>
#include <FlashStorage.h>
#include <RTCZero.h>
#include <DFRobot_PN532.h>
#include <WiFiNINA.h>

const char *ssid = "TP-Link_6C00";
const char *password = "Morrissey2012";
const char *serverIP = "192.168.1.102";
const uint16_t serverPort = 5000;
WiFiClient client;

void resetStorage();
void handleSerialCommand(String command);
void storeTimestamp(byte *uid, int uidLength);
void fetchElapsedTime();

#define  BLOCK_SIZE      16
#define  PN532_IRQ      (2)
#define  INTERRUPT      (1)
#define  POLLING        (0)
#define MAX_ENTRIES 50

DFRobot_PN532_IIC  nfc(PN532_IRQ, POLLING);
DFRobot_PN532:: sCard_t NFCcard;

#define MAX_TIME_DIFF_ENTRIES 10

struct UIDTimeData {
    byte uid[7];
    int uidLength;
    unsigned long loginTimestamps[MAX_TIME_DIFF_ENTRIES];
    unsigned long logoutTimestamps[MAX_TIME_DIFF_ENTRIES];
    int loginIndex = 0;
    int logoutIndex = 0;
    bool isLoggedIn = false;
};

struct StorageData {
    UIDTimeData entries[MAX_ENTRIES];
    int currentIndex;
};

FlashStorage(flashStorage, StorageData);

bool firstScan = true;
RTCZero rtc;
```

Appendix 4. Flask Server Script

Double click script to open in new page.

```
from flask import Flask, request, jsonify
from datetime import datetime
import logging
import re

app = Flask(__name__)

# Path where your Pi logs data
log_file_path = "/mnt/usb/flask_server.log"

# Configure logging to write to the file on the USB drive
logging.basicConfig(
    filename=log_file_path,
    level=logging.INFO,
    format='%(asctime)s UID: %(message)s',
    datefmt='%Y-%m-%d %H:%M:%S'
)



# Regex pattern for your data lines
pattern = (
    r'^(?P<datetime>\d{4}-\d{2}-\d{2} \d{2}:\d{2}:\d{2})'
    r'\s+UID:\s+(?P<uid>\S+)'
    r'\s+\|\s+Name:\s+(?P<name>.*?)'
    r'\s+\|\s+Session
Duration:\s+(?P<hours>\d+)\s+hours,\s+(?P<minutes>\d+)\s+minutes,\s+(?P<seconds>\d+)\s+second
s'
    r'\s+\|\s+Timestamp:\s+(?P<timestamp>.*)$'
)

@app.route('/postdata', methods=['POST'])
def receive_data():
    uid = request.form.get('uid')
    hours = int(request.form.get('hours', 0))
```

Appendix 5. Intensity tracker Arduino Nano 33 IoT Coding

Double click script to open in new page.

```
#include <Arduino_LSM6DS3.h>
#include <ArduinoBLE.h>
#include <LiquidCrystal_I2C.h>
#include <Wire.h>
#include <FlashStorage.h>
#include <FlashAsEEPROM.h>

#define LCD_ADDRESS 0x27
#define LCD_COLUMNS 16
#define LCD_ROWS 2

LiquidCrystal_I2C lcd(LCD_ADDRESS, LCD_COLUMNS, LCD_ROWS);

// IMU data variables
float gyroX, gyroY, gyroZ;
double pitch = 0.0;
double lastPitch = 0.0;
double lastSignificantPitch = 0.0;
unsigned long lastUpdateTime = 0;

// Detection and counting variables
unsigned int cycleCount = 0; // Count of detected cycles (e.g., complete pedal revolutions
in cycling)
unsigned int stepCount = 0; // Count of detected steps (e.g., in walking or running)
unsigned int peaks = 0; // Count of detected peaks in the pitch data, used for cycle/step
detection
const float someSmallValue = 0.5; // Threshold for detecting changes in pitch, small
movements
const float stationaryThreshold = 500.0; // Threshold for determining significant movement
to reset timeout
const float pitchThreshold = 4100.0; // Threshold to differentiate between a step and a
cycle based on pitch
unsigned long firstStepTime = 0; // Time when the first step was detected
bool isStepCountingActive = false; // Flag to indicate if step counting is active
unsigned long firstCycleTime = 0; // Time when the first cycle was detected
bool isCycleCountingActive = false; // Flag to indicate if cycle counting is active
unsigned long lastLCDUpdateTime = 0; // Time when the LCD was last updated
const unsigned long lcdUpdateInterval = 1000; // Update interval in milliseconds (e.g.,
1000ms for 1 second)

const size_t cadenceValuesSize = 30;
float stepCadenceValues[cadenceValuesSize] = {0};
float cycleCadenceValues[cadenceValuesSize] = {0};

unsigned long cadenceTimes[cadenceValuesSize] = {0};

// Timeout mechanism
unsigned long lastActivityTime = 0;
```

Appendix 6. DAIM App Coding

The DAIM mobile application was developed using Android Studio and version-controlled via a private GitHub repository titled "DAIMApp." Full access to the source code is available through a private link (provided below), restricted to read-only permissions. Access is limited to individuals with the direct URL and cannot be searched or indexed publicly.

Repository Access: https://gitfront.io/r/boydy/rziJGeZoMSTb/DAIMapp/

To navigate the application files:

- **Main Application Code:**

  DAIMApp > app > src > main > java > com > example > daimapp

- **User Interface Assets (UI Images):**

  DAIMApp > app > src > main > res > drawable

This structure contains the full implementation of the DAIM app, including Bluetooth communication logic, NFC handling, goal management, UI components, and game mechanics.

Core file names include:

- BluetoothConnection.kt
- DAIMApi.kt
- DataClasses.kt
- ExerciseFragment.kt
- GroupFragment.kt
- MainActivity.kt
- ProfileManager.kt
- ProfileSetupActivity.kt

- QuestionsActivity.kt
- RecordFragment.kt
- RetrofitClient.kt
- RetrofitClientLocal.kt
- SharedViewModel.kt
- TaskManager.kt
- YouFragment.kt

Appendix 7. Detailed DAIM end-to-end architecture

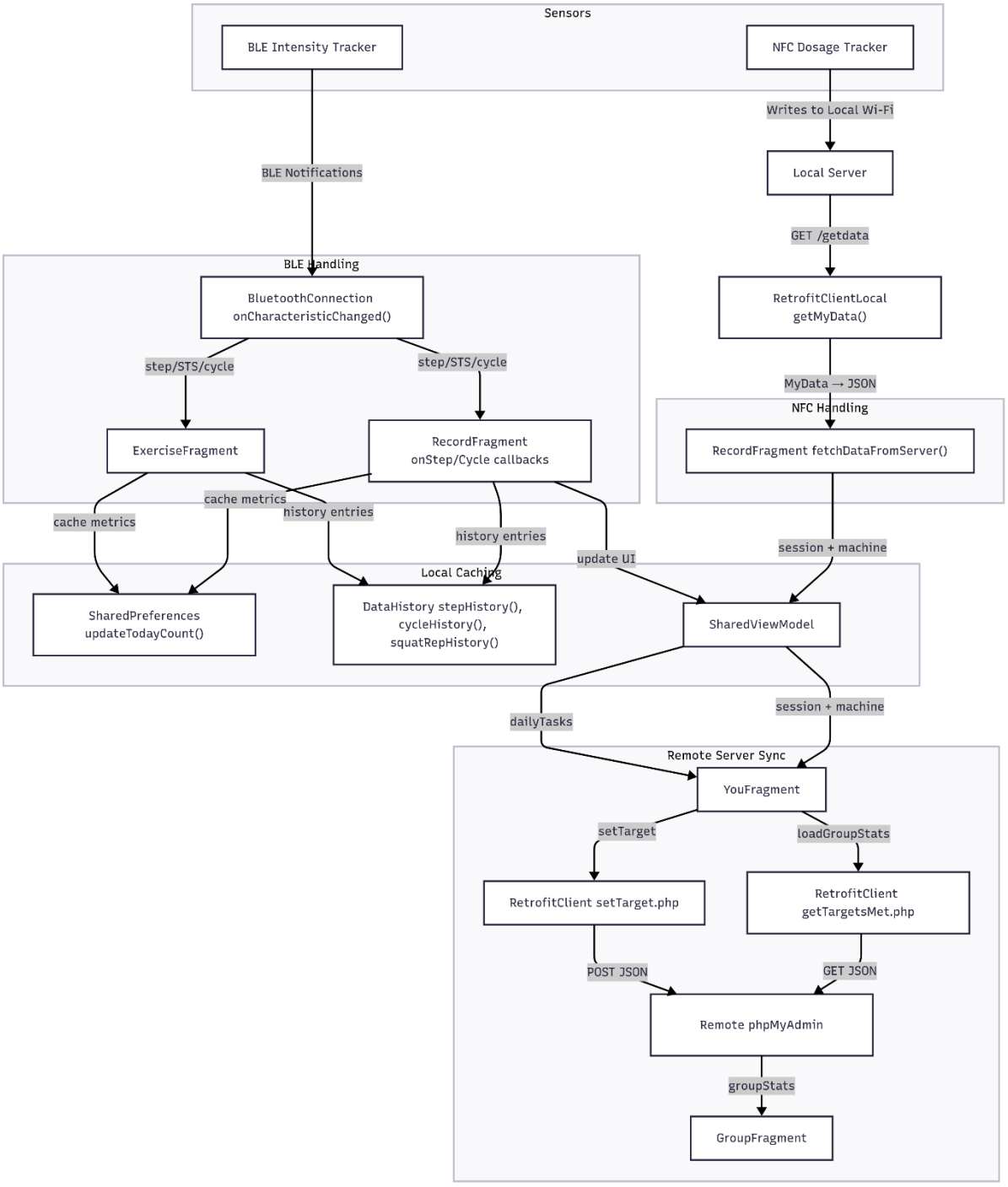

Figure 60 Data-flow architecture of the DAIM application, illustrating sensor inputs, communication and caching layers, core task logic, and remote synchronisation.

Appendix 8. App Accessibility

Table 62 WCAG 2.2 conformance review for the DAIM Android application.

Criteria	Description	How the app addresses this	Pass / Partial/ Needs improvement
1.3.4 Orientation (AA)	Content does not restrict its view and operation to a single display orientation, such as portrait or landscape, unless a specific display orientation is essential.	Nowhere in the Android source is the manifest forced to make the screen portrait or landscape. Every fragment is inflated by 'LayoutInflater' without orientation guards, so the UI re-flows when the user rotates the handset.	Pass
1.4.1 Use of Colour (A)	Colour is not used as the only visual means of conveying information, indicating an action, prompting a response, or distinguishing a visual element.	Feedback uses both numbers and imagery. The record fragment shows number of reps and gamified feedback for STS with successive heart images. Likewise, group status is communicated by text ("Met Target: 3 out of 5") in addition to the coloured tower graphic. Finally the YouFragment uses progress bars with icons of trophies to indicate success.	Pass
1.4.3 Contrast (Minimum) (AA)	The visual presentation of text and images of text has a contrast ratio of at least 4.5:1, except for the following: Large Text, Incidental and Logotypes	The app relies on the default Material 3 dark text on light background, which usually meets 4.5.1. Although, custom drawables' such as the pixel-heart frames and the tower floors have not been separately contrast-checked.	Partial
1.4.10 Reflow (AA)	Content can be presented without loss of information or functionality, and without requiring scrolling in two dimensions for vertical scrolling content at a width	Most screens use ConstraintLayout with flexible constraints. A few views (e.g. addTowerBlockForFloor() hard-codes 200 dp × 150 dp	Partial

	equivalent to 320 CSS pixels and horizontal scrolling content at a height equivalent to 256 CSS pixels.	images) may introduce sideways scroll on very small devices.	
2.5.1 Pointer Gestures (A)	All functionality that uses multipoint or path-based gestures for operation can be operated with a single pointer without a path-based gesture, unless a multipoint or path-based gesture is essential.	Complex gestures are avoided as all actions (start, cancel, save, edit) use standard setOnClickListener taps. Swipe-to-edit in the notes list is optional because the same actions are available by tapping the row to open an Edit dialogue.	Pass
2.5.4 Motion Actuation (A)	Functionality that can be operated by device motion or user motion can also be operated by user interface components and responding to the motion can be disabled to prevent accidental actuation, except when: supported interface or essential	The mobile app does not rely on device shaking or tilting; all controls are buttons or sliders and the IMU resides in the external tracker, not the phone.	Pass
2.5.7 Dragging Movements (AA)	All functionality that uses a dragging movement for operation can be achieved by a single pointer without dragging, unless dragging is essential or the functionality is determined by the user agent and not modified by the author.	Swiping a note left invokes showEditDeleteDialog(), but the same dialogue appears when the user simply taps the note (onEditClick lambda in NotesAdapter). No other drag-only gestures are used.	Pass
2.5.8 Target Size (Minimum) (AA)	The size of the target for pointer inputs is at least 24 by 24 CSS pixels, except when: Spacing, Equivalent, Inline, User Agent Control and Essential.	Primary buttons and ClickableProgressBar all receive default Material padding (48 dp min-width). Some custom icons (heart frames) are non-interactive, so target size is not an issue.	Pass
3.3.7 Redundant Entry (A)	Information previously entered by or provided to the user that is required to be entered again in the same process is either auto-populated, or available for the user to select. Except	User metadata is cached in SharedPreferences, so name/DOB reappear when reopening the profile. updateTodayCount() also ensures daily step totals	Pass

	when: re-entering the information is essential, the information is required to ensure the security of the content, or previously entered information is no longer valid.	carry over between fragments without re-entry.	

Appendix 9. SUS, IMI and UEQ

Please enter your participant number: _____

System Usability Scale (SUS)

This is a standard questionnaire that measures the overall usability of a system. Please select the answer that best expresses how you feel about each statement after using the Logging System today.

	Strongly Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Strongly Agree
1. I think I would like to use this system frequently.	μ	μ	μ	μ	μ
2. I found the system unnecessarily complex.	μ	μ	μ	μ	μ
3. I thought the system was easy to use.	μ	μ	μ	μ	μ
4. I think that I would need the support of a technical person to be able to use this system.	μ	μ	μ	μ	μ
5. I found the various functions in this system were well integrated.	μ	μ	μ	μ	μ
6. I thought there was too much inconsistency in this system.	μ	μ	μ	μ	μ
7. I would imagine that most people would learn to use this system very quickly.	μ	μ	μ	μ	μ
8. I found the system very cumbersome to use.	μ	μ	μ	μ	μ
9. I felt very confident using the system.	μ	μ	μ	μ	μ
10. I needed to learn a lot of things before I could get going with this system.	μ	μ	μ	μ	μ

How likely are you to recommend this system be integrated to the cohort operation procedure? (please circle your answer)

Not at all likely 0 1 2 3 4 5 6 7 8 9 10 Extremely likely

ADAPTED INTRINSIC MOTIVATION INVENTORY

For each of the following statements, please indicate how true it is for you, using the following scale:

1	2	3	4	5	6	7
Not at all true			Somewhat true			Very true

Questions	1	2	3	4	5	6	7
1. I enjoyed using this system very much.							
2. I think I am pretty good at using this system.							
3. I put a lot of effort into using this system.							
4. I did not feel nervous at all whilst using it. (R)							
5. I thought using this system was a boring. (R)							
6. I believe this system could be of some value to me.							
7. I believe I had some choice about using this system.							
8. I didn't try very hard to do well at using the system. (R)							
9. I think that using this system is useful for *tracking my rehabilitation exercises*.							
10. This system did not hold my attention at all. (R)							
11. I felt very tense whilst using the system.							
12. I felt like it was not my own choice to do this task. (R)							
13. I thought this system was quite enjoyable							
14. I would be willing to use this again because it has some value to me.							
15. I am satisfied with my performance at using the system.							
16. It was important to me to do well at using the system.							
17. I used this system because I wanted to.							
18. Using the system was an activity that I couldn’t do very well. (R)							
19. I felt pressured while doing this.							
20. I think doing this activity could help me *to motivate myself in continuing my rehabilitation.*							

Please make your evaluation now.

For the assessment of the product, please fill out the following questionnaire. The questionnaire consists of pairs of contrasting attributes that may apply to the product. The circles between the attributes represent gradations between the opposites. You can express your agreement with the attributes by ticking the circle that most closely reflects your impression.

Example:

attractive	○	⊗	○	○	○	○	○	unattractive

This response would mean that you rate the application as more attractive than unattractive.

Please decide spontaneously. Don't think too long about your decision to make sure that you convey your original impression.

Sometimes you may not be completely sure about your agreement with a particular attribute or you may find that the attribute does not apply completely to the particular product. Nevertheless, please tick a circle in every line.

It is your personal opinion that counts. Please remember: there is no wrong or right answer!

User Experience Questionnaire

Please assess the product now by ticking one circle per line.

	1	2	3	4	5	6	7		
annoying	○	○	○	○	○	○	○	enjoyable	1
not understandable	○	○	○	○	○	○	○	understandable	2
creative	○	○	○	○	○	○	○	dull	3
easy to learn	○	○	○	○	○	○	○	difficult to learn	4
valuable	○	○	○	○	○	○	○	inferior	5
boring	○	○	○	○	○	○	○	exciting	6
not interesting	○	○	○	○	○	○	○	interesting	7
unpredictable	○	○	○	○	○	○	○	predictable	8
fast	○	○	○	○	○	○	○	slow	9
inventive	○	○	○	○	○	○	○	conventional	10
obstructive	○	○	○	○	○	○	○	supportive	11
good	○	○	○	○	○	○	○	bad	12
complicated	○	○	○	○	○	○	○	easy	13
unlikable	○	○	○	○	○	○	○	pleasing	14
usual	○	○	○	○	○	○	○	leading edge	15
unpleasant	○	○	○	○	○	○	○	pleasant	16
secure	○	○	○	○	○	○	○	not secure	17
motivating	○	○	○	○	○	○	○	demotivating	18
meets expectations	○	○	○	○	○	○	○	does not meet expectations	19
inefficient	○	○	○	○	○	○	○	efficient	20
clear	○	○	○	○	○	○	○	confusing	21
impractical	○	○	○	○	○	○	○	practical	22
organized	○	○	○	○	○	○	○	cluttered	23
attractive	○	○	○	○	○	○	○	unattractive	24
friendly	○	○	○	○	○	○	○	unfriendly	25
conservative	○	○	○	○	○	○	○	innovative	26

Appendix 10. Semi-structured Interview Question Schedule

Semi-structured Interview Question Schedule

Stroke Background and Views on Rehabilitation

1. Can you tell me a bit about your stroke experience and the types of rehabilitation you've previously participated in?
2. How would you describe your current rehabilitation routine?
3. What goals are you hoping to achieve through your rehabilitation?
4. Have you previously used any technology or digital tools as part of your rehabilitation? If so, what was your experience with them?
5. What are your expectations or hopes for this study regarding your recovery?

Wearable Tracker Experience

1. How would you describe your experience with the wearable tracker over the past week?
2. Were there any specific challenges you encountered while using the wearable sensor?
3. Did the wearable tracker impact your motivation to engage in physical activity or specific exercises? If yes, how?
4. How comfortable was the wearable device to wear and use during your exercises?
5. Did you find the data collected by the wearable (e.g., repetitions, cadence) helpful for understanding your activity levels?
6. Were there any issues with the Bluetooth connectivity or comfort in wearing the device on your hemiplegic side?

Near-field communication (NFC) Dosage Tracker (for CCRT Participants)

1. How easy or challenging did you find it to use the NFC tracker at the rehabilitation stations?
2. Did the NFC tracking help you stay on track with your rehabilitation activities or goals?
3. How would you describe the role of the NFC tracker in supporting your overall rehabilitation routine?
4. Were there any issues with the NFC system's responsiveness or functionality while tapping in or out of activities?
5. Do you feel the dosage information collected by the NFC tracker was accurate and helpful for understanding your time spent on each exercise?

App Experience

1. How would you describe your overall experience with the app during the study?
2. Was the goal-setting feature helpful in keeping you engaged with your rehabilitation routine? Why or why not?
3. Did you find the app's interface (e.g., navigation, visuals) easy to use and understand?
4. What did you think about the community or peer support aspect within the app? Did it have any effect on your motivation?
5. How often did you refer to the app's suggested rehabilitation tasks, and were they relevant to your goals?
6. Did the app help you feel more in control or informed about your rehabilitation progress?

Closing Questions

1. Reflecting on both the wearable tracker and app, what did you find most beneficial about using these tools in your rehabilitation?
2. Were there any aspects of the wearable tracker, NFC system, or app that you would suggest improving?
3. In what ways, if any, did these tools help you feel more supported in your rehabilitation journey?
4. Would you be interested in using similar tools long-term as part of your rehabilitation, if available?
5. Is there anything else you would like to share about your experience in this study or any additional feedback you have for us?

Semi-structured Interview Question Schedule [APHASIA FRIENDLY]

Stroke Background and Views on Rehabilitation

1. Can you tell me about your stroke?
2. What exercises or therapies are you doing now?
3. What do you want to get better at with these exercises?
4. Have you used technology (like apps or devices) in your therapy before? How was it?

Wearable Tracker Experience

1. How was your experience with the wearable tracker this week?
2. Did you have any problems using it?
3. Did the tracker make you feel more motivated to exercise?
4. Was it comfortable to wear?
5. Did seeing your steps and movement count help you understand your progress?

NFC Dosage Tracker (for CCRT Participants)

1. Was it easy or hard to use the NFC tracker?
2. Did the NFC tracker help you keep up with your exercises?
3. Did it feel useful for tracking time spent on exercises?
4. Was the NFC tracker easy to tap in and out of stations?

App Experience

1. How did you feel about using the app?
2. Did the daily goals help you stay motivated?
3. Was the app easy to use and understand?
4. Did seeing others' progress in the app make you feel more motivated?
5. Did you look at the app's exercises? Were they helpful for your goals?

Closing Questions

1. What did you find most helpful about using the tracker and app?
2. Are there any things you didn't like or would change?
3. Did these tools make you feel more supported in your exercises?
4. Would you want to keep using tools like these for your rehabilitation?

Appendix 11. Interview Answers

Wearable Tracker Experience		
Participant One	**Participant Two**	**Participant Three**
Q1. How would you describe your experience with the wearable tracker over the past week?		
"I liked it when it was working properly. The device like is small and you kind of forget about it, so that I sort of liked. But the constantly pulling it back up was a little bit annoying. "	"For me personally I got a lot of motivation from it. Again, because as much as I mentioned my arm, but my walking is also a big part, the quicker I get, the first thing people notice when they're walking down the street towards you is the limp. So, it causes people to stare. So, for me, I think that it pushed me to the point I actually got the bike out the garage again and was able to get round the estate and get back out on the bike, so for me it gave me a lot of drive and a lot of motivation."	"Yeah, it was good to see what you know, how many steps and things that you've got and once I had it on it felt OK, you know, you get used to it. And then I did keep looking down all the time to see if it's still working, you know but that's just probably me you know." "Uh-huh. All in all, it was a good experience."
Q2. Were there any specific challenges you encountered while using the wearable sensor?		
"Uncomfortable. Like. Uncomfortable… The thigh tracker wasn't uncomfortable, but I needed to pull it up or adjust the Velcro."	"Mostly, a server issue where if you weren't at Strathclyde uni… All I would say about that is because it worked fine the full time we were in the uni."	"Yeah, well I made the mistake by not asking when you said that I could I get the extension thing. So I think I should have had that extension home with me when I was doing it and that would have been better you know, to get on myself without any help." "I think it would have been a belt with the holes in it you know."
Q3. Did the wearable tracker impact your motivation to engage in physical activity or specific exercises? If yes, how?		

“Yeah, I like the step counter, and it reminded me that like how I was stepping when I’m in the house I kind of take an easy route, but the thigh tracker made me aware to lift the knee and focus on my foot.”	“Yeah.” “Just being competitive. And the fact that to me it was like, it was just like a third person sitting there saying ‘get up and get this done’, I knew that the week that I had it the full time if I was in the house just about to have my dinner and I knew I had tasks to do on it was like a third person shouting ‘get this done’ ‘get this done’.”	“Once I had it on, I just forgot about it, you know. Well, the first session I kept looking at it quite a lot, you know, and when I had it in the house, you know “Is it working, is it not”. But when I had had it on in here and I was confident it was working, I just forgot about it.” “I moved more with it on. Because I had the app that supplied with it, the mobile phone. I was aware of the targets set on it so I’d say that did motivate me a little bit.”
Q4. How comfortable was the wearable device to wear and use during your exercises?		
“I felt like the strap was falling down a lot.” “I don't tend to really use this hand a lot so trying it one handed was hard but not impossible. You extended the strap and that helped and I’m pretty good at problem solving so I could work around it.”	“Putting it on was a wee bit challenging because of my left hand, but again I just used it like an exercise. It was like it was another challenge to me. So, I could do it, albeit I've not got full functionary in my hand. It's tough, but I managed to do it. I've just used it like another task.” “It was fairly comfortable. If anything, I would say try and make it a wee bit more slim-lined and maybe add some sort of storage device on it that would naturally store everything. There were concerns sometimes when I thought ‘I wonder if that’s counted my steps’ I kind of felt robbed because I was unsure. But that’s, I’m not going to put that down to the thigh tracker that was just my understanding because I	“It's fine, but I just think it could have been a wee bit lighter, but that's probably because of the size of the battery.”

	wasn't fully aware at the start of how it works."	
Q5. Did you find the data collected by the wearable (e.g., repetitions, cadence) helpful for understanding your activity levels?		
"Yes. Yeah, because I tend to have my phone on me like apple fit tracker and I was under the impression that… that thigh tracker is more sensitive, so it picks up and going about the house and tidying up was a lot more steps than I thought."	"Yeah. Basically, like you say, it lets you see if you are you pushing yourself today are you not pushing yourself today? It also indicated when you are being lazy as opposed to being active."	"Didn't really understand the cycle's but I understood the steps when it was at step mode, then I can tell 500-600 steps but the cycles I didn't really understand what was going on there… But you told me today it means that that one revolution of peddling, so I know now."
Q6. Were there any issues with the Bluetooth connectivity?		
"No."	"So I would just say a bit of teething problems, which you get with everything in life just about so."	"No."

Near-field communication (NFC) Dosage Tracker		
Participant One	**Participant Two**	**Participant Three**
Q1. How easy or challenging did you find it to use the NFC tracker at the rehabilitation stations?		
"No. The cards were easy, I just had to remember to take them with me, yeah."	"The card system was very easy. I think the challenge is that it more our own brains because of the cognitive issue and stuff we forget like, our short-term memory is not amazing, it isn't great. So, it's the constant reminder." "Yeah. But now I think I'm in a bit more of a routine, there has been the odd time that I went on a machine and forgot to tap in. It happened the other day on the treadmill and it destroyed me because I forgot. That's	"I found it easy. It's just a point of remembering to you know, so I suppose if you were doing it constantly then it's like everything repetition, it would stick in your mind, you know." "I would say after two sessions using the card was fine."

	the odd time but. For me personally, it's in my head now." "Would say it took me at least three sessions for me to remember to grab my card."	
Q2. Did the NFC tracking help you stay on track with your rehabilitation activities or goals?		
"Yes because the gym is set up, all of the machines have like designated purpose for stroke, I can't imagine it will have changed… I know when I come here that I work hard, and I don't think the cards necessarily have influenced me to work especially hard."	"Again, yes. It pushes you to get on the machine and get the workout done. Knowing at the back of my mind that all this data is getting collected and you're able to get feedback. So, for me it was definitely motivational."	"Yes."
Q3. How would you describe the role of the NFC tracker in supporting your overall rehabilitation routine?		
"Yeah. I like that. The gym that I used to go to had these sort of challenges and that motivated me too. With competition."	"I would just make the card system mandatory and during the first assessment week we do our consultation and then say, 'guys this is what you do, but you must do this'. Because even for people who aren't as advanced or as driven as I am, it still really good because I can see improvement with other people's movement. So, to be able to give them that feedback at the end of it and give them something to help push because they know they are going on the machines."	"Yes. Yeah."
Q4. Were there any issues with the NFC system's responsiveness or functionality while tapping in or out of activities?		
"No. Just the power banks, I sometimes turned them on."	"No, it's just like, you know it's just like any other card its got its magnetic strip. It's very simple and it works all you need to do hold it for a	"Couple of times. Yes, it didn't work a couple of times but then you sorted it."

	couple of seconds and it does pick it up."	
Q5. Do you feel the dosage information collected by the NFC tracker was accurate and helpful for understanding your time spent on each exercise?		
"Yeah."	"Yes."	"I don't look at that every day, but. Well, I found that OK. It didn't seem like it was in a competition with people. But it's just, it's up to the individual and that, you know, some people don't care to be #1 some people are." "No, I think they're accurate, you know, as long as the person remembers to clock in and clock out."

App Experience		
Participant One	**Participant Two**	**Participant Three**
Q1. How would you describe your overall experience with the app during the study?		
"I liked the targets, I feel like if I haven't exercised for the day, having a target named activity is motivating like 'walk 100 steps'. It's a good way of motivating me."	"The app was fairly simple to use. Again, there was some connection problems, but other than that it was very simple to use."	"It was quite straightforward that you can see what information you wanted on it and then act accordingly. You know your goals were on it. Then you can just double tap on it when you've completed goals and then information is stored OK."
Q2. Was the goal-setting feature helpful in keeping you engaged with your rehabilitation routine? Why or why not?		
"Yeah."	"Yes, but for me, the goals… I'm fit and we are all at different levels, I felt like the goals just weren't challenging enough. They're could be a good different between the difficulty levels. Between beginner, intermediate and expert. I would have a good distance between them so that you	"Yes, because. Set your target and it felt good, it always feels good if you can reach your target."

	actually feel like you've stepped up." "Personally. Would like more goals."	
Q3. Did you find the app's interface (e.g., navigation, visuals) easy to use and understand?		
"Yeah, yeah."	"Yes it was very simple to use. There was no confusion on the screen, so yes."	"Yes, basically it says that you're doing your activities out with Strathclyde uni or in it, you're actually doing it, and so that was clear."
Q4. What did you think about the community or peer support aspect within the app? Did it have any effect on your motivation?		
"I felt pressure and if somebody else was meeting their targets and I had not, then I would feel pressure like I had let the team down." "No, because… Yes and no, I feel like time to do the stuff yes, like when I have time to do the stuff, but no if I am clocking on at night and I was tired to do my exercises yeah. Saturday morning I could have the whole day but late at night no because then I'd have targets to meet and…" "I'd rather high score just to work on my high score as when I see fit."	"No, It definitely helped. All I would say is on that feature, it would maybe be better to pair people up that is just as driven as you. I think that maybe someone who had a better connection with." "For me, I like the fact that the both of them are there. Because when you are at home that's got… I would have like to have been paired up with someone that had the same level of drive as me. Because I was looking at it and I was looking at the tasks completed bit, and I was thinking 'come on participant'."	"I think you can look at it two ways. One, you're cooperating with the other person or else you're in direct competition with them. So it depends what your nature is I suppose, your frame of mind, thinking, but I suppose both ways would help, you know to motivate you, you know, because you're trying to help and my way of thinking was that the other person's had their stroke so I need to try and help them. So if we're helping each other that's the way I was being cooperative instead of trying to beat the other person. But I suppose the other way the both are getting the same result at the end of the day."
Q5. How often did you refer to the app's suggested rehabilitation tasks, and were they relevant to your goals?		
"Yes. But I would want more." "Yeah, longer tasks, yes."	"Constant." "Yeah. Yeah." "If I'm going to the gym doing legs you'd do like three sets and then double	"I just did it once a day." "They concentrated a lot more on my legs, I thought instead of my arms. So maybe it would have to be tailor made for the stroke

	them up so for me I'd like to see it reflect more of a gym workout plan."	patient, what their affected limbs are."
Q6. Did the app help you feel more in control or informed about your rehabilitation progress?		
"Yes, the note feature."	"It was good for not having to bend down as much to see what you were doing, but I think in this day and age we all walk around with our phones 24/7 so it's easy just to flip the phone on and have a look."	"Yes, that was good to have it to refer to. Yeah."

Closing Questions		
Participant One	**Participant Two**	**Participant Three**
Q1. Reflecting on both the wearable tracker and app, what did you find most beneficial about using these tools in your rehabilitation?		
"The most beneficial. The thigh tracker."	"The tacker played a big part for me as well because it got me out cycling. I would say out of the full thing I would have to give it to the thigh tracker and the app."	"I preferred the community feature." "The tap-in-tap-out boxes."
Q2. Were there any aspects of the wearable tracker, NFC system, or app that you would suggest improving?		
"The thigh tracker."	"The app."	"I've made two suggestions about the thigh tracker, so the thigh tracker, actually three suggestions."
Q3. In what ways, if any, did these tools help you feel more supported in your rehabilitation journey?		
"Yeah, like if I had had it when I came out of hospital, I would have felt like… Coming out of the hospital, you feel like very on your own. So, I think the thigh tracker and the app would have felt like more community."	"It gave me a lot of motivation."	"Yes. Yeah."

Q4. Would you be interested in using similar tools long-term as part of your rehabilitation, if available?		
“Yeah.”	“Yes.”	“If it came in the market and it was on Amazon, yes, I would order it from Amazon, Next day delivery.”
Q5. Is there anything else you would like to share about your experience in this study or any additional feedback you have for us?		
“No.”	“No.”	“No, I think you've covered it.”

Appendix 12. INDEX Breakdown

Table 63 Alignment of this project's development activities with the INDEX study actions recommended by the MRC Framework (Cathain et al., 2019).

INDEX framework action (Cathain et al., 2019)	**Key activities carried out in this project**	**Related thesis chapter(s)**
Plan the development process	• Conducted a narrative review to understand how rehabilitation dosage & intensity are measured, examine wearables/telerehab literature, and explore intervention-development and co-design methods. • Ran focus groups to elicit user needs regarding dose/intensity tracking. • Mapped design criteria against the project timeline and produced a flow-chart of the development process.	2 & 3
Involve stakeholders (deliverers, users, beneficiaries)	• Held online focus groups (aphasic & non-aphasic stroke survivors, AHP, family member) to gather needs and co-create design requirements. • Adopted co-design for iterative development of every DAIM component.	3
Bring together a team & establish decision-making processes	• Researcher acted as sole developer; therefore, formal team structures were limited. • Emphasised co-design to incorporate stakeholder feedback into decisions throughout development.	(Embedded across project)
Review published research evidence	• Performed a narrative review on dose/intensity measurement, wearables, and telerehabilitation.	2
Draw on existing theories	• Reviewed literature on intervention-development frameworks and co-design methodology to guide approach.	2 & 3
Articulate programme theory	• Developed and continually refined a flow-chart linking design criteria, timelines, and expected mechanisms of change; revisited throughout development.	2 – 7
Undertake primary data collection	• Collected feasibility, validity, usability, and acceptability data during system iterations.	4, 5 & 7

Understand context	• Evaluated feasibility and acceptability of the DAIM in clinical, community, and home settings.	4, 5 & 7
Plan for future real-world implementation	• Considered clinical measurement practices, telerehab evidence, and stakeholder requirements from the outset; maintained co-design across the DAIM life cycle to facilitate adoption.	2 – 5 & 7
Design and refine the intervention	• Derived device criteria from stakeholder Focus Groups. • Iteratively adjusted hardware/software through feasibility, validity, usability, and acceptability studies.	3 – 5 & 7
End the development phase	• Synthesised all studies in the thesis and discussed implications of the DAIM.	8

Appendix 13. Ethic Approvals & Research Passport

Outlook

Approval: UEC22/94 Kerr: Feasibility of a user-centred collaborative mobile application to support home-based rehabilitation of people recovering from Stroke: a focus group study

From Ethics <ethics@strath.ac.uk>
Date Mon 30/01/2023 15:35
To Fiona Boyd <fiona.boyd.2016@uni.strath.ac.uk>
Cc Andrew Kerr <a.kerr@strath.ac.uk>; Ethics <ethics@strath.ac.uk>

Dear Fiona

ETHICAL AND SPONSORSHIP APPROVAL
UEC22/94 Kerr: Feasibility of a user-centred collaborative mobile application to support home-based rehabilitation of people recovering from Stroke: a focus group study

I can confirm that the University Ethics Committee (UEC) has approved this protocol and appropriate insurance cover and sponsorship have now also been confirmed.

I remind you that the UEC must be informed of any changes you plan to make to the research project, so that it has the opportunity to consider them. Any change of staffing within the research team should be reported to UEC.

The UEC also expects you to report back on the progress and outcome of your project, with an account of anything which may prompt ethical questions for any similar future project and with anything else that you feel the Committee should know.

Any adverse event that occurs during an investigation must be reported as quickly as possible to UEC and, within the required time frame, to any appropriate external agency.

The University agrees to act as sponsor of the above mentioned project subject to the following conditions:

1. That the project obtains/has and continues to have University/Departmental Ethics Committee approval.
2. That the project is carried out according to the project protocol.
3. That the project continues to be covered by the University's insurance cover.
4. That the project complies with Scottish Government restrictions and University guidance in relation to Covid-19 procedures and permissions.
5. That the Director of Research and Knowledge Exchange Services is immediately notified of any change to the project protocol or circumstances which may affect the University's risk assessment of the project.
6. That the project starts within 12 months of the date of this letter.

As sponsor of the project the University has responsibilities under the UK Policy Framework for Health and Social Care Research. You should ensure you are aware of those responsibilities and that the project is carried out according to the UK Policy Framework.

On behalf of the Committee, I wish you success with this project.

Kind regards

Angelique

Angelique Laverty
University Ethics Committee Manager
Research & Knowledge Exchange Services (RKES)
University of Strathclyde
Room 3.01, Graham Hills Building
50 George Street
Glasgow
G1 1QE

ethics@strath.ac.uk

http://www.strath.ac.uk/rkes

University of Strathclyde Glasgow

THE QUEEN'S ANNIVERSARY PRIZES 2019 & 2021
For Higher and Further Education

UNIVERSITY OF THE YEAR 2012 & 2019
Times Higher Education

SCOTTISH UNIVERSITY OF THE YEAR 2020
The Times & The Sunday Times

Outlook

Amendment Approval: RE UEC20/08 User Experience of a Technology Based Rehabilitation Programme - Generic Framework

From Ethics <ethics@strath.ac.uk>
Date Tue 25/04/2023 11:08
To Andrew Kerr <a.kerr@strath.ac.uk>
Cc Fiona Boyd <fiona.boyd.2016@uni.strath.ac.uk>; Daniel Nicol (Student) <daniel.nicol.2018@uni.strath.ac.uk>

Dear Andy

I can confirm that the University Ethics Committee has approved the amendment to this protocol and appropriate insurance cover and sponsorship are confirmed.

I remind you that the Committee must be informed of any changes that are made to the research project, so that it has the opportunity to consider them. The Committee also expects you to report back on the progress and outcome of your project, with an account of anything which may prompt ethical questions for any similar future project and with anything else that you feel the Committee should know.

The University agrees to act as sponsor of the above mentioned project subject to the following conditions:

1. That the project obtains/has and continues to have University/Departmental Ethics Committee approval.

2. That the project is carried out according to the project protocol.

3. That the project continues to be covered by the University's insurance cover.

4. That the project complies with Scottish Government restrictions and University guidance in relation to Covid-19 procedures and permissions.

5. That the Director of Research and Knowledge Exchange Services is immediately notified of any change to the project protocol or circumstances which may affect the University's risk assessment of the project.

6. That the project starts within 12 months of the date of this letter.

As sponsor of the project the University has responsibilities under the UK Policy Framework for Health and Social Care Research. You should ensure you are aware of those responsibilities and that the project is carried out according to the UK Policy Framework.

On behalf of the Committee, I wish you success with this project.
Kind regards

Angelique

Angelique Laverty
Research Ethics and Governance Manager
Research & Knowledge Exchange Services (RKES)
University of Strathclyde

ethics@strath.ac.uk

https://www.strath.ac.uk/research/researchknowledgeexchangeservices/universityethicscommittee/

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2020
The Times & The Sunday Times

Outlook

Approval: UEC24/108 Kerr: Feasibility of Co-designed Telehealth Platform using Wearable Telemonitoring Sensor to Support Remote Self-rehabilitation in Stroke Recovery

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From Ethics <ethics@strath.ac.uk>
Date Thu 09/01/2025 15:13
To Andrew Kerr <a.kerr@strath.ac.uk>; Fiona Boyd <fiona.boyd@strath.ac.uk> cc
Ethics <ethics@strath.ac.uk>

Dear Fiona

ETHICAL AND SPONSORSHIP APPROVAL

UEC24/108 Kerr: Feasibility of Co-designed Telehealth Platform using Wearable Telemonitoring Sensor to Support Remote Self-rehabilitation in Stroke Recovery

I can confirm that the University Ethics Committee (UEC) has approved this protocol and appropriate insurance cover and sponsorship have now also been confirmed.

I remind you that the UEC must be informed of any changes you plan to make to the research project, so that it has the opportunity to consider them. Any change of staffing within the research team should be reported to UEC.

The UEC also expects you to report back on the progress and outcome of your project, with an account of anything which may prompt ethical questions for any similar future project and with anything else that you feel the Committee should know.

Any adverse event that occurs during an investigation must be reported as quickly as possible to UEC and, within the required time frame, to any appropriate external agency.

The University agrees to act as sponsor of the above mentioned project subject to the following conditions:

1. That the project obtains/has and continues to have University/Departmental Ethics Committee approval.

2. That the project is carried out according to the project protocol.

3. That the project continues to be covered by the University's insurance cover.

4. That the project complies with Scottish Government restrictions and University guidance in relation to Covid-19 procedures and permissions.

5. That the Director of Research and Knowledge Exchange Services is immediately notified of any change to the project protocol or circumstances which may affect the University's risk assessment of the project.

6. That the project starts within 12 months of the date of this letter.

As sponsor of the project the University has responsibilities under the UK Policy Framework for Health and Social Care Research. You should ensure you are aware of those responsibilities and that the project is carried out according to the UK Policy Framework.

On behalf of the Committee, I wish you success with this project.

Kind regards

Angelique

Angelique Laverty
University Ethics Committee Manager
Research & Knowledge Exchange Services (RKES)
University of Strathclyde
Room 3.01, Graham Hills Building
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The Times & The Sunday Times

Fiona Boyd
Postgraduate Student
University of Strathclyde
Department of Biomedical Engineering
Wolfson Centre
106 Rottenrow
Glasgow
G4 0NW

R&D Department
David Matthews Building
Monklands Hospital
Monkscourt Avenue
AIRDRIE
ML6 0JS

Date: 18/12/2023
Enquiries to: Claire McKenzie, R&D Facilitator
Email: Claire.mckenzie@lanarkshire.scot.nhs.uk

Dear Fiona,

Project: [L23114]: Technology enriched stroke rehabilitation in acute/sub-acute stroke

Letter of Access (LoA) for a non-NHS researcher to carry out research

NOTE: Please complete sections 1 and 2 on Page 1 of this LoA and return it to the R&D Department at the above address. The R&D Manager will countersign and return Page 1 to you. The LoA becomes active only when you receive the countersigned Page 1, which you should attach to this letter as confirmation of your access to conduct research.

This letter confirms your right of access to conduct research through NHS Lanarkshire for the purpose and on the terms and conditions set out below. This right of access commences on 18th December 2023 and ends on 1st November 2024 unless terminated earlier in accordance with the clauses below.

You have a right of access to conduct such research as confirmed in writing in the NHS Lanarkshire R&D Management Approval letter for the above named research project. Please note that you cannot start the research until the Chief Investigator for the research project has received a letter from NHS Lanarkshire giving permission to conduct the project.

While undertaking research through NHS Lanarkshire you will remain accountable to your place of study, University of Strathclyde, but you are required to follow the reasonable instructions of Gillian Sweeney, Occupational Therapy Advanced Practitioner, in NHS Lanarkshire or those given on her behalf in relation to the terms of this right of access.

You must supply the appropriate member of staff in your Human Resources Department with a copy of this Letter of Access. Your **place of study** must inform **NHS Lanarkshire** if it becomes aware of any issues that impact on your suitability or ability to carry out your agreed research activities within **NHS Lanarkshire.** This includes, but is not limited to, situations where PVG Scheme/Disclosure Scotland/CRB Disclosure vetting/criminal records check information suggests that you may have become unsuitable to do regulated work.

You are required to co-operate with NHS Lanarkshire in discharging its duties under the Health and Safety at Work etc Act 1999 and other health and safety legislation and to take reasonable care for the health and safety of yourself and others while on NHS Lanarkshire premises. You must observe the same standards of care and propriety in dealing with patients, staff, visitors, equipment and premises as is expected of any other contract holder and you must act appropriately, responsibly and professionally at all times.

You are required to have the appropriate Occupational Health Clearance for the research activities that you will undertake within NHS Lanarkshire, including, but not limited to, appropriate immunisation; Health clearance has been undertaken in line with Scottish Government Health Clearance document - Health Clearance for Tuberculosis, Hepatitis B, Hepatitis C and HIV for New Healthcare Workers with Direct Clinical Contact with Patients (2008) / or where relevant; Department of Health England Health Clearance document - Health Clearance for Tuberculosis, Hepatitis B, Hepatitis C and HIV: new healthcare workers (2007). Immunisation screening has been undertaken in line with Immunisation against Infectious Disease – The Green Book (2013).

You are required to ensure that all information regarding patients or staff remains secure and *strictly confidential* at all times. You must ensure that you understand and comply with the requirements of the NHS Confidentiality Code of Practice (http://www.wdhscp.org.uk/media/1256/revised-code-of-confidentiality-final.pdf) and relevant UK-GDPR and Data Protection 2018 legislation. Furthermore, you should be aware that unauthorised disclosure of information is an offence and such disclosures may lead to prosecution.

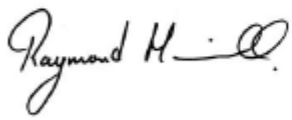
You should ensure that, where you are issued with an identity or security card, a bleep number, email or library account, keys or protective clothing, these are returned upon termination of this arrangement. Please also ensure that while on the premises you wear your ID badge at all times, or are able to prove your identity if challenged. Please note that NHS Lanarkshire accepts no responsibility for damage to or loss of personal property.

We may terminate your right to attend at any time either by giving seven days' written notice to you or immediately without any notice if you are in breach of any of the terms or conditions described in this letter or if you commit any act that we reasonably consider to amount to serious misconduct or to be disruptive and/or prejudicial to the interests and/or business of this NHS organisation or if you are convicted of any criminal offence. Your place of study is responsible for your conduct during this research project and may in the circumstances described above instigate disciplinary action against you.

NHS Lanarkshire will not indemnify you against any liability incurred as a result of any breach of confidentiality or breach of the UK-GDPR and Data Protection legislation. Any breach of the UK-GDPR and Data Protection legislation may result in legal action against you and/or your place of study.

If your current role or involvement in research changes, or any of the information provided in your Research Passport changes, you must inform your employer through their normal procedures. You must also inform your nominated manager in NHS Lanarkshire.

Yours sincerely



Raymond Hamill
Senior Research & Development Manager

NAME	TITLE	SITE	ROLE
Gillian Sweeney	Occupational Therapy Advanced Practitioner	Gillian.Sweeney@lanarkshire.scot.nhs.uk	Principal Investigator
Dr Andrew Kerr	Senior Lecturer	a.kerr@strath.ac.uk	Chief Investigator
Angelique Laverty	Research Ethics and Governance Manager	ethics@strath.ac.uk	Sponsor Contact
Lili Ghekiere	Assistant HR Advisor	aurelie.ghekiere@strath.ac.uk	HR Contact