PROJECT PROPOSAL

2025/6 Academic Entry Year – Cohort 4

Supervisory Team

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Project Details

Title: Developing a deep learning-based model to predict rehabilitation outcomes in underserved groups living with multiple long-term conditions

Summary: This project will develop a deep learning-based model (DLM) that can predict who successfully completes exercise-based rehabilitation in individuals with multiple long-term conditions (MLTCs, the coexistence of two or more long-term conditions) and who may need personalized support. MLTCs are increasingly prevalent amongst ethnic minorities and socioeconomically disadvantaged groups. These individuals face numerous adverse outcomes, including reduced quality of life and

increased healthcare utilisation. While exercise-based rehabilitation improves outcomes for many long-term conditions, adherence rates vary, and early drop-out is common.

DLMs are complex networks that learn independently, applying algorithms to data to identify patterns. DLMs have shown promise in predicting rehabilitation outcomes in other conditions but have yet to be applied to large, diverse populations with MLTCs. This project will use real-world rehabilitation data to cluster participants into groups based on successful rehabilitation outcomes, defined through consensus. Differences between groups will be analysed to develop a deep learning model that predicts program completion. Interviews with those who were unable to complete their programs will identify barriers and facilitators, informing personalised support strategies. The goal is to provide healthcare professionals with tools to deliver more equitable, tailored care for underserved populations, improving outcomes across diverse communities.

Aim: The aim of this project is to develop a deep learning-based model (DLM) to predict who successful completion of exercise-based rehabilitation in a diverse cohort with multiple long-term conditions (MLTCs), and who may require personalized support to improve completion and outcomes.

Background: The global prevalence of people living with MLTCs (the coexistence of two or more chronic conditions) is growing.[1] This increase disproportionately impacts ethnic minorities[2], and who are socioeconomically disadvantaged.[3,4] MLTCs are associated reduced quality of life, physical function, loss of independence and increased healthcare utilisation[5-12]. Although exercise- based rehabilitation improves outcomes across many long-term conditions[13] adherence to these programmes remains low[14], and premature discontinuation high in people with MLTCs.[15]

DLMs have shown promise in predicting rehabilitation completion and outcomes in several long-term conditions[16-20], but has yet to be applied to large real-world datasets including socioeconomically and ethnically diverse MLTC populations.[18] Implementing DLMs in this population may enable healthcare professionals to better support individuals with MLTCs at risk of early drop-out and poorer post rehabilitation outcomes.

Research Plan:

Year 1: A consensus process with a diverse group of stakeholders (people with MLTCs, carers, healthcare professionals and commissioners) will defines 'successful' completion of rehabilitation.

Year 2-3: Data from real-world rehabilitation programmes (cardiac, pulmonary, chronic kidney disease and arthritis), will be used to cluster participants with MLTCs into distinct groups based on the definition of 'successful' rehabilitation. Baseline differences in routinely collected demographic characteristics (e.g., ethnicity, socioeconomic status), patient-reported outcome measures (PROMs), and objective tests (e.g., exercise capacity, physical function, physical activity) will be explored. These data will then inform the development and implementation of a DLM capable of predicting successful rehabilitation completion.

Year 3: The experiences of people with MLTCs who were unable to successfully complete rehabilitation, using the definition defined in year 1, will be explored through semi-structured interviews. These will identify personal barriers and facilitators to programme completion, as well as service-level influences on adherence. Purposive sampling will ensure maximum variation. Interviews will be audio-recorded, transcribed and analysed using reflexive thematic analysis. Findings will guide the development of bespoke support packages for people with MLTCs at risk of non-completion.

Expected outcomes and impact: This project will enable healthcare professionals to accurately predict who may require additional support to maximise the benefits of rehabilitation. The expected impact is to increase equity of support for underserved populations. In addition to the supervisory team, the participant will be supported by Dr Claire Lawson (clinical epidemiologist and nurse lecturer at University of Leicester), Professor Mike Hurley (Professor of Rehabilitation Sciences at Kingston University and St George's University of London) and Professor Sharlene Greenwood (Honorary Professor and Consultant Renal Physiotherapist at Kings College London). We will also collaborate with a medical ethicist to ensure the work does not inadvertently lead to gatekeeping of resources, or perpetuate systematic inequalities.[2,21]

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