Personalised Stroke Rehabilitation: An AI Pipeline for Exercise Programmes Using a Co-Designed Decision Support Tablet Application

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Keywords: Stroke Rehabilitation, Applied Artificial Intelligence, Decision Support System, Assistive Technology

Abstract: Stroke rehabilitation requires personalised and continuously adapted exercise programmes, resulting in significant therapist involvement and is often impractical for patients recovering at home in community settings. This motivates the need for assistive tools and decision support systems to enhance efficiency and rehabilitation progress. This position paper presents an integrated pipeline combining a therapist-informed tablet application with artificial intelligence (AI) models to support therapists in decision-making. Co-designed with stroke therapists, HCI researchers, AI experts, and PwS, the application captures baseline and weekly reassessment data, including BBS, TUG, pain, perceived difficulty, and FITT prescriptions, across 4–6 week cycles to determine whether to progress, sustain, or regress exercises. To facilitate early model development, we created a clinically informed synthetic dataset (n = 336 sessions across 5 PwS profiles over 12 weeks) that simulates functional progression and therapist decision-making patterns. This dataset reflects key features identified through workshops with clinicians and PwS, capturing essential assessment metrics such as stroke characteristics, functional scores, therapist goals, patient feedback, exercise difficulty, repetitions, duration, body area, FITT parameters, and exercise recommendations. We trained and evaluated models to predict weekly progression decisions. Logistic regression achieved a weighted F1-score of 51.6%, while a multilayer perceptron reached 79.3% and a decision tree 90.2%. Clinical data will be collected in the next stage of the project (5–8 PwS, 4–6 weeks) and integrated with the synthetic dataset using real–synthetic fusion. Future work includes exploring generative AI for richer rehabilitation trajectories and validating models through an ongoing clinical study. Overall, this work advocates for AI-augmented tools in rehabilitation informatics to support scalable, patient-centred stroke care in the community.

1 Introduction

Stroke remains one of the leading causes of death and long-term disability worldwide, with profound implications for healthcare systems and individual quality of life. In 2025, the global burden of stroke is staggering, affecting an estimated 13.7 million people annually and incurring costs exceeding US$890 billion, with projections indicating a near-doubling by 2050.(Feigin et al., 2025). Effective rehabilitation is critical for mitigating these impacts, as timely and personalised interventions can restore motor function, enhance independence, and reduce secondary

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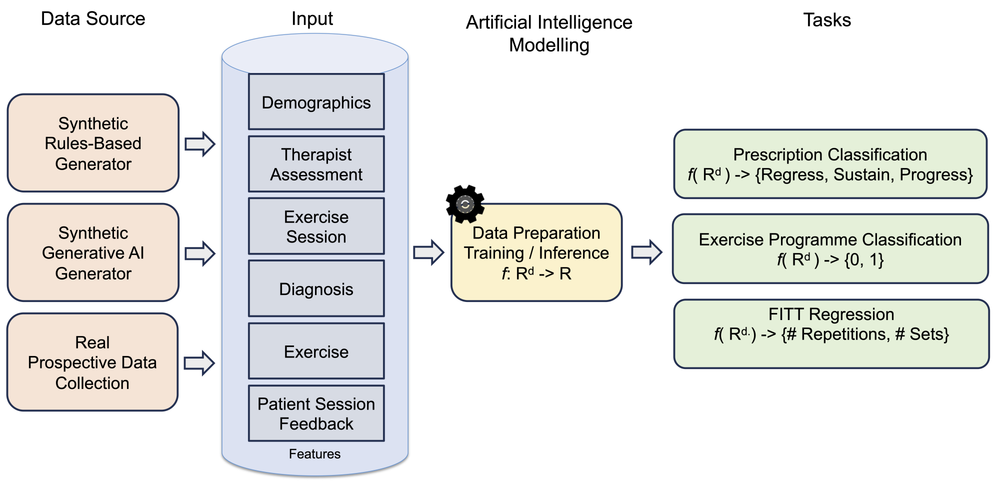

Figure 1: Stroke Rehabilitation - Artificial Intelligence Pipeline

complications such as falls. However, traditional stroke rehabilitation approaches face significant barriers. Programmes must be highly tailored to individual needs, requiring substantial therapist involvement that is often resource-intensive and geographically constrained. For persons with stroke (PwS) recovering in the community, where over 80% of rehabilitation occurs post-discharge (American Stroke Association, 2025), these approaches are impractical, leading to suboptimal adherence and outcomes.

The advent of digital health technologies and artificial intelligence (AI) offers a transformative opportunity to address these challenges. By integrating AI with wearable sensors, cameras, mobile applications, and decision-support systems, AI-augmented tools can enable scalable, patient-centred care that bridges the gap between clinical expertise and everyday recovery. Such innovations align with the growing emphasis on assistive technologies, home monitoring, and physiological/behavioural modelling in health informatics, fostering equitable access and personalised care(Verma et al., 2022; Thayabaranathan and Cadilhac, 2025). However, no existing pipeline integrates patient feedback, exercises, and therapist assessments with AI to assist in generating exercise programmes.

In this position paper, as depicted in Figure 1, we advocate for an integrated AI pipeline designed to enhance exercise management in stroke rehabilitation. Our tablet-based application is being co-designed with stroke therapists, HCI researchers, AI experts and PwS. Therapists prescribe exercises via frequency, intensity, duration, and type (FITT principles). The application will capture data across a 4–6 week rehabilitation cycle, including initial assessments (e.g., Berg Balance Scale and Timed Up-and-Go scores), patient demographics, diagnosis details, and session feedback on exercise difficulty, fatigue, and pain. The application will support therapists by recommending changes to exercise programmes during assessments. The therapist will be able to make the final decision on the AI-prescribed recommendations before assigning to the PwS. The input features to the AI model include demographics, therapist assessments, exercise sessions, diagnoses, and patient feedback. The AI models will address the following (supervised machine learning) tasks, where the model takes d features.

- Classification: predict exercise progression $f : \mathbb{R}^d \rightarrow \{\text{Regress, Sustain, Progress}\}$
- Classification: predict exercise prescription $f : \mathbb{R}^d \rightarrow \{0, 1\}$
- Regression: predict FITT $f : \mathbb{R}^d \rightarrow \{\text{\# Repetitions}, \text{\# Sets}\}$

Collectively, these tasks enable the application to generate personalised exercise programme recommendations. In our initial evaluation using a rule-based synthetic dataset, a range of linear and non-linear models were assessed to balance predictive performance with interpretability. While linear baselines performed modestly, non-linear models more effectively captured the encoded therapist decision rules, with the decision tree achieving a weighted F1-score of 90.2%. These results highlight our approach's potential to improve stroke rehabilitation in the community. Our contributions are as follows.

- A co-designed, user-centred tablet application that operationalises rehabilitation informatics workflows for community-based stroke care.

- A rule-based, clinically informed synthetic dataset that enables early experimentation and model development prior to real clinical data collection.
- An evaluation of supervised machine learning models and structured ML pipelines for exercise progression decision-support, comparing interpretable linear and non-linear approaches, including logistic regression, multilayer perceptrons, and decision trees.
- Preliminary findings demonstrating strong alignment between non-linear model predictions and encoded therapist logic, motivating further HCI refinements and planned clinical studies for equitable deployment.

2 Background and Related Work

2.1 Stroke Rehabilitation Informatics

Stroke remains a leading cause of death and disability worldwide, with millions of new cases each year and substantial long-term motor functional impact (Feigin et al., 2025). Throughout the acute, inpatient, and community phases of care, survivors frequently experience persistent impairments in balance, gait, coordination, and mobility that call for organised, goal-oriented rehabilitation. In order to monitor recovery and facilitate transitions into community and home-based rehabilitation, current national guidelines emphasise the importance of progressive, high-intensity therapy, frequent evaluation of rehabilitation potential, and the use of validated measures (Intercollegiate Stroke Working Party, 2023). Validated tests such as the Timed Up-and-Go (TUG) test and the Berg Balance Scale (BBS) are used in standard rehabilitation practices and assessments. While the TUG offers a dependable timed measure of fundamental mobility and change over time, the BBS captures important aspects of postural stability and has shown strong associations with functional and motor performance. (Berg et al., 1992; Podsiadlo and Richardson, 1991).

2.2 Artificial Intelligence and Decision Support in Stroke Rehabilitation

Artificial intelligence is increasingly integrated across the stroke rehabilitation support, from accelerated imaging interpretation to technologies supporting neurological and functional recovery (Chandrabhatla et al., 2023). In rehabilitation, growing evidence has shown how ML and sensor-based approaches can model motor performance and personalise therapy adjustments (Senadheera et al., 2024). UK policy initiatives further reveal a progressive increase for AI-enabled decision support, with early deployments improving workflow speed and recovery outcomes in clinical practice (Department of Health and Social Care, 2022). Collectively, these advances highlight the potential for AI to augment therapist decision-making and extend timely, individualised support into community and home-based rehabilitation.

Despite rapid advancements, the majority of AI systems in stroke rehabilitation are still restricted to discrete prediction tasks such as predicting outcomes or categorising mobility rather than supporting the day-to-day decisions involved in adapting exercises or managing rehabilitation programmes. Research in human–AI collaboration shows that interactive systems, which allow therapists to review, refine, and guide model outputs, can improve assessment accuracy and align more closely with clinical reasoning (Lee et al., 2021; Turmo Vidal et al., 2025). However, these design principles have yet to be extended into practical, stroke-specific tools capable of informing individual exercises or supporting session-to-session adjustments in real-world rehabilitation.

2.3 Co-Design, Data Structures, and Digital Infrastructure

Human-centred and co-design approaches are essential for ensuring that digital rehabilitation tools align with therapist reasoning, patient needs, and practical use in community-based recovery. Thematic analysis and participatory design methods help surface requirements and translate therapy experiences into application interfaces and workflows that support both clinicians and PwS (Braun and Clarke, 2021; Adam et al., 2019). This is especially important in stroke rehabilitation, where motor, cognitive, and sensory changes influence how people use technology and perform prescribed exercises, as observed clearly reflected during prototype testing in our workshops.

Although telerehabilitation can extend therapist oversight into the home, many existing systems remain limited to basic exercise delivery or simple check-ins, often still paper-based, with little integration of structured assessments, patient feedback, or detailed prescription data (Kringle et al., 2023). National guidelines further call for interoperable digital infrastructure, clear goal-setting, and continuity of care across hospital, community, and remote settings (National Institute for Health and Care Excellence, 2023; Intercollegiate Stroke Working Party, 2023).

Cross-platform applications provide a strong foundation for this objective. Organising clinical information around entities such as *Patient*, *Therapist*, *Assessment*, *Exercise*, and *Session* enables rich, longitudinal datasets that capture both clinical progress and engagement, supporting AI-driven personalisation.

2.4 Gap in Literature and Motivation for an Integrated AI Pipeline

Although telerehabilitation has expanded access to remote therapy sessions, current assistive systems majorly focus on basic communication or simple exercise delivery and limited support to the depth of assessment, feedback capturing, and iterative adaptations, which is essentially needed for day-to-day stroke rehabilitation progress (Kringle et al., 2023). Similarly, advances in AI have shown positive outcomes for modelling motor performance and predicting rehabilitation needs, yet most applications remain task-specific and do not operate within a unified workflow that connects therapist expertise, patient-reported information, and per-session weekly data (Senadheera et al., 2024). Equity-focused research further highlights that digital innovations must be designed to close, rather than widen, gaps in access, particularly for community-based stroke survivors who already face barriers to sustained rehabilitation (Verma et al., 2022).

Addressing these gaps, this work proposes an integrated, AI-enabled rehabilitation pipeline that incorporates supervised learning models, structured data collection, and a co-designed digital application. The objective is to provide PwS with individualised program management and exercise progression in community settings. The co-design procedure, creation of a synthetic dataset with clinical knowledge, and preliminary assessment of the machine learning elements integrated into this pipeline are described in the following sections.

3 Methodology

This work develops a decision-support pipeline for community stroke rehabilitation, integrating co-design, structured data modelling, clinically grounded synthetic data generation, and supervised machine learning. The workflow comprises four core components: (i) Assessment metrics elicitation, (ii) a relational rehabilitation data model, (iii) Rule-based clinically informed synthetic dataset generation, and (iv) supervised machine learning models predicting and reflecting therapist decision-making.

3.1 Co-Design and Assessment metrics elicitation

Workshops were conducted with stroke therapists, PwS, and HCI researchers to identify the data needed for weekly progression decisions and how it is to be captured within the tablet application. Therapists prioritised core assessments (BBS, TUG), symptom feedback from the patient(pain, perceived difficulty), goal-setting fields, and FITT prescription parameters after each exercise is completed in the session. These sessions also shaped the broader data flow from baseline assessment through weekly review and informed how model outputs should be surfaced to clinicians without automating decision-making.

3.2 Structured Rehabilitation Data Model

The co-design process informed a relational schema connecting six entities: *Patient*, *Therapist*, *Assessment*, *Exercise*, *Prescription*, and *Session* (Figure 2). Assessments capture functional scores and goals; prescriptions encode FITT parameters and exercise assignments; and sessions record pain, difficulty, repetitions, and duration. This structure aligns with real rehabilitation workflows and provides a stable foundation for consistent, longitudinal feature extraction required by machine-learning models.

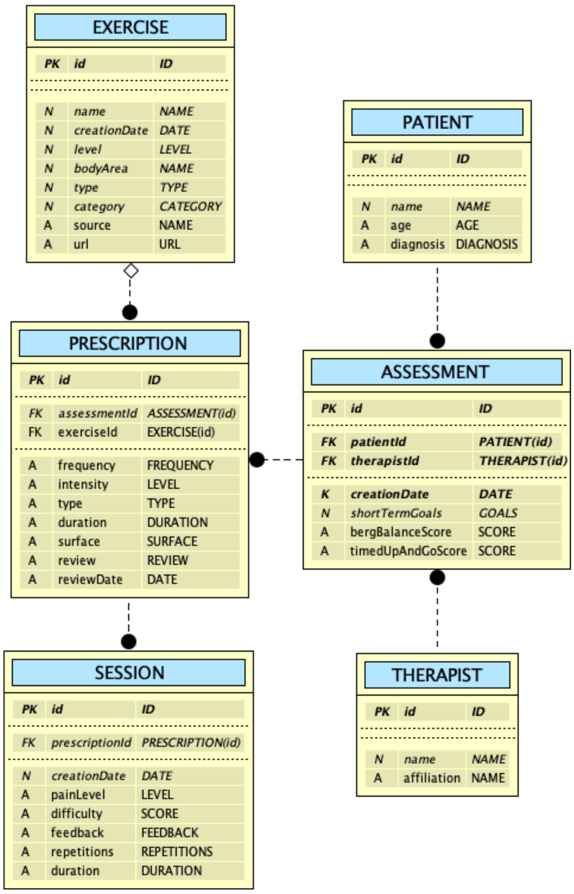

Figure 2: Entity Relationship Diagram (ERD) illustrating the data model linking patient, therapist, and exercise session entities.

3.3 Rule-based Clinically Informed Synthetic Dataset Generation

As real-world application data collection forms the next stage of the project, we developed a clinically informed rule-based generator to simulate exercise-level rehabilitation patterns. The generator initialises each patient with demographics and functional baselines (BBS, TUG, range of motion), sampled from clinically discussed distributions reflecting typical community settings. Each patient is then assigned a multi-exercise programme (three to six exercises) drawn from the Next Step rehabilitation exercise video repository, which organises exercises into three progression levels across major stroke-affected body areas, categories, difficulty, equipment, and defined progression/regression links enabling clinically meaningful sequencing.

Weekly updates combine the latent clinical state BBS, TUG, range of motion, pain, perceived difficulty, and current FITT dose into a readiness score in $[0,1]$. This score incorporates functional capacity, time since stroke, dose effects, and pain penalties. It is mapped to a *true* recommendation $y^{\text{true}} \in \{\text{Regress}, \text{Sustain}, \text{Progress}\}$ using probabilistic rules with per-patient balancing to ensure realistic mixes of progression, sustaining, and regression. Controlled label noise produces an observed label y^{obs}, modelling documentation variability near borderline or high-pain scenarios. Clinical evolution (changes in BBS, TUG, range of motion, pain, FITT duration) follows y^{true}, and a closed-loop titration rule adjusts FITT frequency or intensity based on pain and recent progress. Exercise programmes evolve accordingly: progressing, regressing, or sustaining. Per-exercise outputs include repetitions, duration, patient feedback, therapist feedback, and updated assessments, creating a progression-based exercise-level dataset suitable for model development.

3.4 Machine-Learning Approaches

As outlined in the Introduction, the pipeline focuses on three supervised machine learning tasks that reflect weekly therapist decisions within community rehabilitation. Each model receives a feature vector of d inputs derived from demographics, assessments, FITT prescriptions, exercise attributes, and patient-reported feedback.

The first task predicts whether an exercise should be *Regressed*, *Sustained*, or *Progressed*. The second determines whether the programme structure should change (e.g., add or remove exercises). The third estimates personalised dosage targets, such as repetitions, number of sets (sessions) and per-exercise duration, for the following week. Formally, these tasks correspond to:

$$f_1 : \mathbb{R}^d \to \{\text{Regress,Sustain,Progress}\},\ f_2 : \mathbb{R}^d \to \{0,1\},\ f_3 : \mathbb{R}^d \to \mathbb{R}^2$$

We assess baseline models such as logistic regression, naïve Bayes, multilayer perceptrons, and decision trees to investigate feasibility using our synthetic dataset, providing an early indication of how these approaches may support real-time decision-making once in-app clinical data become available.

4 Application

4.1 System Architecture and Data Flow

The decision-support pipeline is deployed within a cross-platform Flutter application designed for both therapists and PwS. With co-designing insights, the interface was iteratively prototyped to reflect real rehabilitation workflows while remaining accessible for individuals with motor, cognitive, or visual limitations, and also to incorporate feedback from PwS and their caregivers on the app functionalities could be added that were not part of their usual rehabilitation, such as the ability to provide and track their feedback, monitor their progress, and more. The app collects routine clinical and patient-reported data in both community and home settings, serving as the primary data-collection mechanism for the project's later stages.

Therapists can review AI-derived recommendations and adjust prescriptions through an administrative interface that consolidates assessments, functional histories, symptom trends, and programme details, ensuring that clinical judgement remains central and that any AI-generated routine is validated and refined by the therapist before being assigned. PwS complete daily or weekly sessions, record performance for each exercise or session, and report symptom feedback using a simplified interface. Real-time synchronisation of all interactions with the backend allows for tracking in accordance with the structured data model described in Methodology.

The patient-facing feedback screen (Figure 3) enables PwS to record repetitions, duration, pain, perceived difficulty, fatigue, and posture-related observations. These data fields directly support weekly progression analysis and are informed by validated symptom and activity measures reported in the literature (Pindus et al., 2018; Kunkel et al., 2015). An optional text-based feedback field allows individuals to describe discomfort, emotional factors, or contextual challenges in their own words, adding qualitative depth that can later support NLP-focused modelling and analyses of access to rehabilitation services (Verma et al., 2022; NHS England, 2023; Farooqi and et al., 2022).

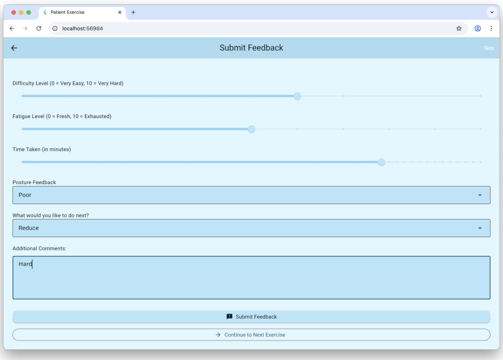

Figure 3: Patient Feedback Screen interface for providing pain, difficulty, fatigue, repetitions, and duration.

4.2 Model Integration and Decision Support

At each reassessment point, the application merges functional assessments, symptom trends, exercise attributes, and recent session performance into a structured feature vector that is forwarded to the analytics layer. The deployed models produce three outputs: an exercise-level recommendation (*Progress*, *Sustain*, or *Regress*); a programme-level classification indicating whether exercises should be added or removed; and updated FITT dosage estimates for the exercises that remain. These outputs appear in the therapist interface as decision-support prompts rather than prescriptive instructions, preserving clinical reasoning and reflecting principles of human–AI collaboration (Lee et al., 2021; Lee et al., 2022; Turmo Vidal et al., 2025).

A forthcoming clinical pilot involving 5–8 PwS over 4–6 weeks will deploy the system in *shadow mode*, where model outputs are recorded but do not influence clinical decision-making. This approach allows direct comparison between algorithmic recommendations and therapist judgement, while also examining how the system fits into routine practice and how acceptable it is within community settings (Kringle et al., 2023; American Stroke Association, 2025; Thayabaranathan and Cadilhac, 2025). As real-world data become available, the influence of synthetic and generative samples will be progressively reduced, enabling a safe and equitable transition toward clinically aligned, AI-supported rehabilitation workflows (Verma et al., 2022; NHS England, 2023; Department of Health and Social Care, 2022).

5 Results

The synthetic dataset generated realistic rehabilitation dynamics across 336 sessions and five PwS profiles, with ages ranging from 45 to 80 years and 60–72 recorded sessions per individual. These profiles exhibited clinically coherent diversity: younger individuals (e.g., 45–57 years) showed faster early gains, while older individuals (77–80 years) demonstrated more gradual progress and higher variability in pain and difficulty ratings. Across all profiles, higher pain consistently increased perceived difficulty and reduced repetitions, while BBS and TUG improvements were most prominent during the first two weeks before stabilising. TUG performance reliably differentiated *Progress* from *Sustain/Regress* decisions in a manner consistent with established mobility markers in community rehabilitation. The resulting label distribution - 41% Sustain, 33% Progress, 25% Regress—aligned closely with expected therapist decision patterns, and patient-specific proportions (e.g., Patient 2 with 50% Sustain; Patient 4 with 33% Regress) further confirmed the internal coherence of the generator.

Table 1: Performance of baseline models on prescription classification.

Model	Type	Weighted F1
Logistic Regression	Linear	0.516
Naïve Bayes	Stochastic	0.476
MLP	Neural Network	0.793
Decision Tree	Non-linear	0.902

As shown in Table 1, the non-linear models, particularly the Multi-Layer Perceptron with a weighted F1-score of 79.3% and the Decision Tree reaching 90.2%, substantially outperformed the linear and stochastic baselines. Logistic Regression achieved 51.6% and Naïve Bayes 47.6%, reflecting their difficulty in capturing the non-linear, threshold-based relationships embedded in the recovery patterns. Given this imbalance, the weighted F1-score was adopted as the primary evaluation metric, clearly highlighting the advantage of non-linear approaches in modelling the nuanced decision rules present in the synthetic dataset.

Notably, the Decision Tree demonstrated both superior accuracy and strong interpretability: as illustrated in Figure 4, the model first splits on *Perceived Difficulty* (≤ 3.5) to distinguish manageable sessions from those where patients report higher strain. When difficulty is low, the subsequent split on *Week Number* (≤ 4.5) reflects expected early-phase improvements, predicting *Progress* in the initial weeks and *Regress* once gains begin to plateau. When difficulty is high, the tree evaluates functional mobility using the *TUG Score* (≤ 15.4), sustaining exercises when mobility remains adequate and regressing them when slower TUG times indicate reduced stability or higher fall

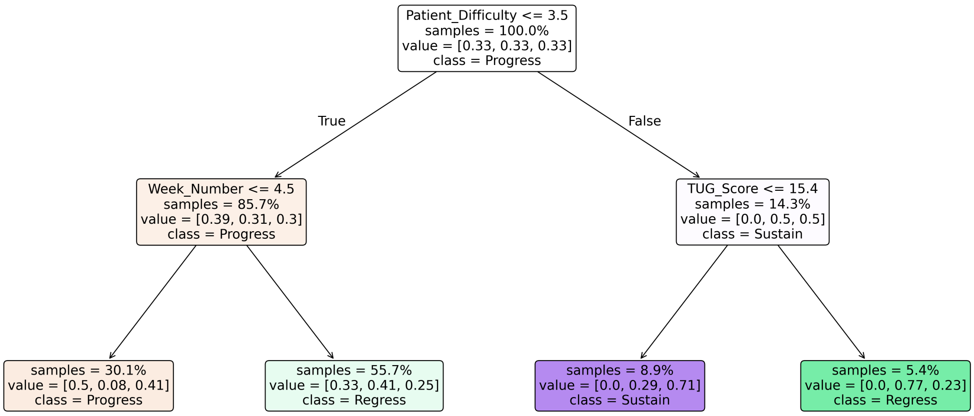

Figure 4: Interpretable decision tree illustrating the dominant features influencing weekly exercise recommendations.

risk. These learned thresholds mirror therapist heuristics, showing that the model captures clinically meaningful nuances embedded within the synthetic dataset.

Two additional components of the pipeline programme-level classification (exercise add/remove decisions) and FITT multi-output prediction—were successfully prototyped and will be fully validated using real data in the upcoming 5–8 PwS clinical pilot. An NLP pipeline for analysing therapist and patient free-text feedback will be incorporated once real-world annotations are available, and a conditional diffusion model is planned to generate richer and more diverse recovery scenarios, improving robustness on rare progression patterns and downstream ML tasks. Overall, these developments position the pipeline for real-world data collection and clinical validation.

6 Acknowledgments

This work was supported by the National Institute for Health and Care Research (NIHR) through the Invention for Innovation (i4i) Programme (NIHR209066): Co-design of an artificial intelligence algorithm for personalised exercise videos to enhance community-based rehabilitation for people with stroke.

7 Conclusion

This position paper has presented a co-designed, AI-enabled pipeline to support exercise programme management for persons with stroke in community settings. Grounded in rehabilitation guidelines and human-centred design, the tablet application integrates therapist-facing and patient-facing interfaces with a structured data model spanning patients, assessments, prescriptions, sessions, and exercise-level feedback. Using this schema, we developed a clinically informed synthetic dataset that encodes functional progression, symptom reports, and therapist decision patterns, enabling early experimentation with supervised machine learning models before large-scale clinical deployment. Our initial modelling results demonstrate that non-linear approaches, particularly decision trees and multilayer perceptrons, can effectively capture the threshold-based and non-linear relationships that determine and interpret the weekly progression decisions. The correspondence between the learned tree structure and clinical reasoning validates the synthetic generator and highlights the potential of AI models to augment rather than replace therapist judgment.

Next, the data collection using the application will be implemented in a clinical pilot involving 5–8 PwS over 4–6 weeks, operating in a real setting to compare algorithmic recommendations with actual therapist decisions and assess usability in routine community practice. Clinical data collected during this pilot will be integrated with the synthetic dataset through real–synthetic fusion, while NLP and generative AI including diffusion models will support richer interpretation of free-text feedback and enable simulation of diverse rehabilitation trajectories. To ensure AI-generated recommendations translate into tangible, comprehensible actions, the graded video-based exercise repository can be expanded to cover additional stroke-affected body areas and more nuanced progression levels.

Overall, this work advocates for co-designed, clinician-centred AI as an assistive decision-support system, strengthening therapist decision-making and enabling safe, scalable, and clinically grounded community stroke rehabilitation.

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