Toward Trustworthy Human-AI Collaboration in Neurorehabilitation: A Multimodal Data Registry for Clinical Decision Support

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Abstract. Regaining independent walking ability is a primary goal after stroke or spinal cord and brain injuries, yet selecting appropriate technological interventions remains a complex challenge. While a human-in-the-loop clinical decision support system (CDSS) can enhance clinical judgement, current real-world data is too fragmented to train trustworthy models. This paper presents a standardised, multimodal data registry prospectively capturing patient characteristics, clinical assessments, and device parameters, providing the foundational infrastructure to develop and validate a reliable, AI-based CDSS for gait neurorehabilitation.

Keywords: Clinical decision support system, Human-in-the-loop, Neurorehabilitation, Gait rehabilitation, Data registry, Rehabilitation technology

1 Introduction

Lasting gait deficits are among the most prevalent consequences of stroke, traumatic brain injury, and spinal cord injury [1]. Therefore, regaining the ability to walk independently is one of the most common functional goals in rehabilitation. Such recovery depends on intensive, repetitive, task-specific training [2]. While robotic exoskeletons and body-weight-support systems can help sustain this intensity [3], they also increase the complexity of clinical decision-making. Clinicians must match each device's configurable settings to the individual patient and available evidence, while guidelines still disagree on which technology is suitable for whom and in what dosage [4]. A human-in-the-loop

clinical decision support system (CDSS) could support therapists' clinical reasoning by combining machine-learned patterns with clinical judgement [5]. For such a system to be trustworthy and clinically applicable, the underlying model must be trained using data reflecting real-world practice [6]. However, in neurorehabilitation, the clinical and device records remain fragmented and are inconsistently documented [7]. Therefore, we present a standardised, multimodal, multicentre data registry for gait rehabilitation interventions, which prospectively captures patient characteristics, routine clinical assessments, and rehabilitation device parameters, supporting the development of a human-in-the-loop CDSS.

2 Methods

The registry was developed as part of D-BOOST^2, a project focusing on technology-assisted neurorehabilitation, supported by the Swiss National Science Foundation [8]. Through user-centred co-design [9], rehabilitation scientists, physical therapists, occupational therapists working in research and clinical practice as well as researchers with expertise in applied mathematics and data science collaborated to ground the registry in clinical workflows while preserving subsequent analytical distinctions. We modelled the therapy session as a recurring decision event, adapting the patient-in-the-loop framework of Cashaback et al. [10] by adding two elements that our analysis identified as essential but implicit: evidence- and safety-based guardrails, and goal setting. The latter was identified in a qualitative study investigating clinical decisions in technology-supported neurorehabilitation [11], as the primary driver of treatment choice. We mapped this framework onto documentation domains (i.e., patient status, goals, and intervention parameters). Subsequent candidate variables were identified by collecting variables shared across clinics. These were then prioritised on the basis of therapists' ratings of their perceived influence on outcomes, and cross-referenced against consensus-based core outcome sets [12]. The resulting instruments were iteratively refined by the team through several review rounds.

3 Results

The resulting data dictionary contains 174 fields across the three instruments implemented in REDCap [13] spanning the care episode (81 baseline, 64 session, and 29 discharge), of which 147 capture data. Coded vocabularies are used throughout, such as the International Classification of Functioning, Disability and Health [14] for goals and the Spinal Cord Injury–Interventions Classification System [15] for interventions. A derived 24-table analytical schema harmonises repeated assessments and preserves missing values to support a human-in-the-loop recommendation model of interventions and dosing.

4 Conclusion

This multicentre registry aims to bridge the gap between routine therapy documentation and the data machine-learning models need to reflect real-world practice. By capturing the full spectrum of gait rehabilitation interventions, the registry will provide a standardised framework for linking patient-level characteristics and clinical assessments with device-level intervention parameters. As neurorehabilitation moves toward precision rehabilitation [16,17], this foundation will support the integration of reliable human–AI collaboration into clinical practice. Ultimately, this will enable therapists to make more consistent, personalised, and outcomes-oriented decisions in gait neurorehabilitation.

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