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Beyond the Therapeutic Cliff: A Clinical Engineering Framework for AI-Driven Home-Based Neurorehabilitation in Rural Veterans

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Abstract
The therapeutic cliff, defined as the steep drop in rehabilitation intensity once a patient leaves inpatient care, is a documented driver of poor functional recovery after stroke and traumatic brain injury. For rural veterans, distance to specialised care, broadband disparity, and fragmented access amplify the drop. We propose a clinical engineering framework for AI-driven home-based neurorehabilitation grounded in SEIPS 2.0 sociotechnical principles. The framework integrates a wearable inertial measurement layer, an artificial intelligence exercise-quality and dose-tracking layer, a fall-prediction subsystem, a caregiver interface layer, and a Veterans Health Administration Care Coordination Home Telehealth integration layer. We synthesise eighteen peer-reviewed sources, map architecture components to validated evidence, and specify deployment constraints for rural cohorts including a bandwidth-tiered profile and a polytrauma-compatible cognitive guardrail. Validation pathways and policy implications for telerehabilitation reimbursement parity are outlined.

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1. Introduction

The dose-response relationship in neurorehabilitation is one of the better-established findings in rehabilitation science. Veerbeek and colleagues synthesised four hundred sixty-seven randomised trials of post-stroke physical therapy and concluded that high-intensity, repetitive, task-specific training produces the strongest motor outcomes [2]. The American Heart Association and American Stroke Association guideline by Winstein and colleagues codifies that conclusion into formal practice standards [3]. Langhorne, Bernhardt, and Kwakkel framed the broader evidence base in their canonical Lancet review [1]: stroke recovery is, to a meaningful degree, dose-dependent and time-sensitive.

Real-world delivered dose, however, falls far short of guideline-level intensity. Lang and colleagues documented that even in-hospital therapy averaged only thirty-two upper-limb repetitions per session [4]. The drop-off accelerates after discharge. Young, Holman, and Cramer, working with the STRONG cohort, quantified the post-discharge dose collapse and showed that it is partially predicted by clinical factors, not random [5].

The phrase therapeutic cliff describes the intensity surface between these two regimes. Inpatient-phase doses are already sub-guideline. Home-phase doses, in the absence of structured monitoring, fall further still. Functional recovery follows the cliff downward.

For the rural veteran cohort, three additional layers of disadvantage stack onto this baseline. First, rural residents have higher stroke incidence and mortality even after risk-factor adjustment [12]. Second, rural veterans have measurably lower internet access and lower stated preference for telemedicine modalities than their urban counterparts [13]. Third, the veteran population carries a distinctive burden of traumatic brain injury and polytrauma, with long-term functional outcomes that demand sustained therapy intensity [16]. The cliff is steepest exactly where the access surface is roughest.

2. Motivation

Three near-term forces make a structured response to the rural-veteran therapeutic cliff both necessary and tractable.

The first is the maturity of artificial intelligence and wearable sensing applied to neurorehabilitation. Mahmoud and colleagues report meta-analytic evidence that AI-augmented physical therapy is non-inferior to, and in several endpoints superior to, conventional therapy for upper-limb outcomes [6]. Tozlu and colleagues demonstrate machine-learning prediction of individual motor impairment trajectories with clinical-grade accuracy [7]. O'Brien and colleagues show that wearable inertial sensors combined with machine learning raise community-ambulator recall in stroke survivors from approximately eighty-five percent to between eighty-nine and ninety-three percent [8]. Seo and colleagues report that a wrist inertial measurement unit paired with a dynamic-time-warping classifier flags compensatory upper-limb movement at home with ninety-two percent accuracy [9]. The wearable-rehab field, as mapped by Kim and colleagues [10] and Maceira-Elvira and colleagues [11], has crossed from laboratory feasibility into deployable clinical decision support.

The second is the operational precedent of the Veterans Health Administration in home-based telehealth. The Care Coordination Home Telehealth (CCHT) program documented by Darkins and colleagues showed a twenty-five percent reduction in bed-days and a nineteen percent reduction in admissions across more than seventeen thousand veterans with chronic conditions [14]. A subsequent matched-cohort study showed mortality reduction from sixteen point six to nine point eight percent in CCHT enrollees [15]. CCHT remains, by enrolled volume and longevity, the largest operational home-telehealth platform in the world. It has, however, never been extended into structured motor neurorehabilitation.

The third is policy ferment. Telehealth reimbursement parity, expanded during the COVID-19 emergency, has partially persisted. Civilian home-health agencies such as Amedisys are actively absorbing rural neuro-rehab caseloads that would once have been handled by hospital-based outpatient clinics. The infrastructure decisions made now will determine whether AI-driven home rehab becomes a defensible standard of care or a fragmented set of pilot deployments.

3. Objectives

This paper has five objectives.

1. Define the therapeutic cliff operationally for rural-veteran neurorehabilitation patients, distinguishing it from generic post-discharge dose drop-off.
2. Specify a clinical engineering framework, grounded in the SEIPS 2.0 sociotechnical model [18], that treats the rural veteran's home as the primary rehabilitation work system.
3. Map each architectural layer of the framework to validated AI, wearable, and telehealth evidence.
4. Define rural-feasible deployment constraints, including a bandwidth-tiered profile and polytrauma-compatible cognitive guardrails.
5. Outline a validation pathway and policy levers needed to translate the framework into Veterans Health Administration and civilian rural-home-health practice.

4. Statement of Contribution

The contributions of this paper are five.

1. **Integrative synthesis:** This is the first paper, to our knowledge, to integrate three previously separate literatures: AI-augmented motor rehabilitation, Veterans Health Administration home telehealth, and rural veteran healthcare disparities. Each literature has matured independently and none has previously been positioned as a connected whole.
2. **Sociotechnical architecture:** The framework is explicitly grounded in SEIPS 2.0 [18] and identifies the patient, the caregiver, the home environment, and the home-health clinician as a connected work system rather than as isolated actors.
3. **Bandwidth-tiered deployment profile:** A three-tier deployment specification is defined, ranging from broadband-rich urban deployment through fixed-wireless rural deployment to satellite-only or store-and-forward deployment, with explicit data-payload and inference-locality choices for each tier.
4. **Polytrauma-compatible cognitive guardrail:** A specific guardrail is defined for the polytrauma and traumatic-brain-injury cohort that disproportionately characterises the veteran population, addressing the cognitive-load constraint that limits adoption of complex rehab technology in this group.
5. **Validation and policy roadmap;** Specific outcome thresholds, comparator arms, and reimbursement levers are identified for translation, rather than a generic call for further research.

5. Methods

This paper is a structured narrative review combined with a clinical engineering framework synthesis. The narrative review draws on a literature search performed across PubMed, Cochrane Library, IEEE Xplore, OpenAlex, and Semantic Scholar between January 2008 and April 2026. Search terms combined “stroke”, “traumatic brain injury”, “rehabilitation”, “telerehabilitation”, “wearable sensor”, “machine learning”, “artificial intelligence”, “veterans”, “rural”, “home telehealth”, and “Care Coordination Home Telehealth”. Reference lists of included reviews were screened for additional sources. Inclusion criteria required peer review, English-language publication, and direct relevance to one of the framework's architectural layers or deployment-context constraints. Predatory journals, Beall-listed sources, and publications without verifiable digital object identifiers or PubMed identifiers were excluded.

Eighteen sources met inclusion and form the citation backbone. The framework synthesis applied SEIPS 2.0 as the sociotechnical scaffold and used a layered architecture template adapted from clinical decision support engineering practice. Each architectural layer was mapped to at least one validated source from the bibliography before inclusion in the framework. The bandwidth-tiered profile was derived from rural-veteran broadband data [13], adjusted against operational CCHT enrolment characteristics [14, 15].

This is not a primary trial, a systematic review under PRISMA, or a clinical implementation study.

The framework is a design proposal positioned for prospective validation, not an evaluated intervention.

6. Results

The framework comprises five architectural layers and three transverse constraints. Table I anchors each layer to its supporting evidence. Table II specifies the bandwidth-tiered deployment profile. Table III maps the framework to the populations of greatest immediate relevance. Figure 1 shows the architecture schematically.

Table 1: Framework Layers and Evidence Anchors

Layer	Function	Supporting evidence
L1. Wearable sensing	IMU motion capture, repetition counting, gait segmentation, compensation detection	[8, 9,10, 11]
L2. AI processing	Exercise-quality classification, dose tracking, impairment-trajectory prediction, fall prediction	[6, 7, 9]
L3. Decision support	Clinician dashboards, threshold alerts, dose-titration recommendations	[3, 5]
L4. Caregiver interface	Prompted exercise delivery, adherence logging, escalation pathway	[3]
L5. CCHT integration	Telehealth visit cadence, secure messaging, longitudinal data store	[14, 15]

Table 2: Bandwidth-Tiered Deployment Profile

Tier	Bandwidth context	Inference locality	Data payload	Population
T1	>= 25 Mbps down	Cloud or hybrid	Continuous video + raw IMU	Suburban / near-urban veterans
T2	5–25 Mbps fixed-wireless or LTE	Edge device + cloud sync	Compressed IMU streams + key-frame video	Rural veterans with stable cellular
T3	Satellite, intermittent, store-and-forward	Edge-only inference	Daily summary uploads, no live video	Most-rural / off-grid veterans

Table 3: Framework Mapping to Target Populations

Population	Primary clinical concern	Layer emphasis	Guardrail emphasis
Stroke, sub-acute rural veteran	Motor recovery dose	L1, L2, L3	Dose-tolerance
Stroke, chronic rural veteran	Sustained adherence	L4, L5	Falls, dropout
Polytrauma and TBI	Cognitive load + motor + behavioural	L1, L4, L5	Cognitive
Aging veteran with comorbidities	Falls + chronic disease coupling	L1 + L5	Falls

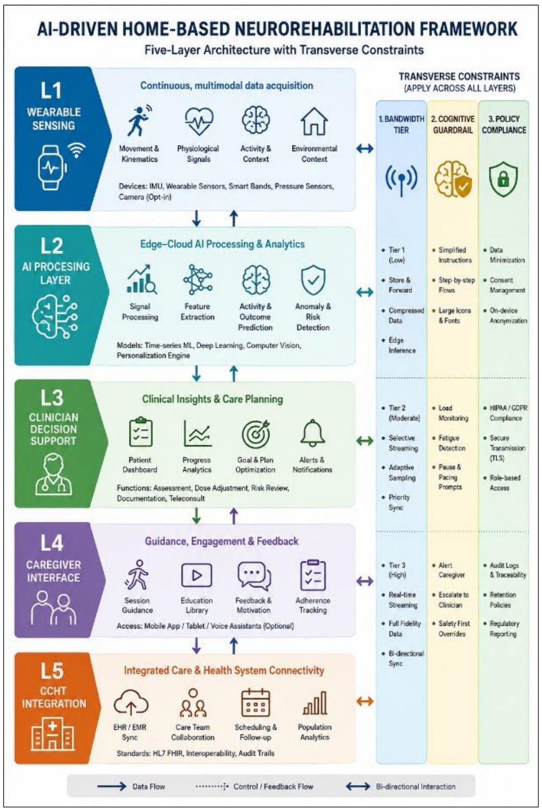

Fig 1: Five-layer architecture of the AI-driven home-based neurorehabilitation framework, showing wearable sensing (L1), AI processing (L2), clinician decision support (L3), caregiver interface (L4), and CCHT integration (L5), with three transverse constraints: bandwidth tier, cognitive guardrail, and policy compliance.

6.1. Layer 1: Wearable Sensing

The framework's sensing layer relies on inertial measurement units placed on the wrist, ankle, and trunk. The wrist IMU drives upper-limb repetition counting and compensation detection per Seo *et al*. 2024 [9], which reports ninety-two percent accuracy in flagging compensatory movement during home-based task practice. The ankle IMU supports gait segmentation and walking-function prediction per O'Brien *et al.* 2022 [8]. The trunk IMU contributes to balance and fall-precursor classification. The sensing layer outputs structured kinematic features rather than raw signals where bandwidth permits, and outputs daily summary features only at Tier 3 bandwidth.

6.2. Layer 2: AI Processing

The processing layer ingests structured kinematic features and produces three classes of output: exercise-quality classification (correct, near-correct, compensatory) using dynamic time warping or transformer-based classifiers as in Seo *et al.* [9]; dose-tracking time series using repetition counts and active-minute estimates calibrated to AHA/ASA dose recommendations [3]; and individualised impairment-trajectory forecasts informed by Tozlu *et al.* [7]. Fall prediction operates as a secondary classifier in this layer, fed by trunk and ankle features, with a precision-favouring threshold suited to the home setting where false positives carry low cost and false negatives carry high cost.

6.3. Layer 3: Decision Support

The decision-support layer presents a clinician dashboard that summarises dose adherence relative to plan, exercise-quality drift, and fall-precursor trends. Threshold-driven alerts trigger telehealth contact. Dose-titration recommendations are surfaced as suggestions, not autonomous adjustments, preserving clinician authority. The dashboard operates within VA secure-messaging compliance and is designed for fifteen-second status comprehension by a clinician carrying a typical home-health caseload.

6.4. Layer 4: Caregiver Interface

The caregiver interface delivers prompted exercise content via a low-cognitive-load mobile or tablet application. It logs adherence, supports voice-only confirmation for low-vision or low-literacy caregivers, and escalates to clinician contact when red-flag thresholds are crossed. The interface design follows SEIPS 2.0 work-system principles [18] by treating the caregiver as a defined system actor whose workload, capacity, and motivation must be designed for, not assumed.

6.5. Layer 5: CCHT Integration

The CCHT integration layer ties the framework into the existing VHA Care Coordination Home Telehealth platform [14, 15]. CCHT supplies the longitudinal data store, the secure-messaging channel, and the established care-coordinator role. The framework extends rather than duplicates CCHT, adding motor-rehab sensing and analytics to a platform whose chronic-disease-monitoring outcomes are already established. Civilian home-health agencies such as Amedisys would substitute their own electronic health record and home-health communication platforms in this layer.

6.6. Transverse Constraints

Three constraints operate across all layers. The bandwidth tier (Table II) determines inference locality and data payload. The cognitive guardrail bounds caregiver-interface complexity and adjusts content pacing for polytrauma and TBI patients [16]. The policy-compliance constraint governs data residency, billing-eligible service definitions, and reimbursement-aligned documentation.

7. Discussion

7.1. Implications for VHA Practice

The framework extends an already-successful CCHT model rather than competing with it. CCHT reduced bed-days, admissions, and mortality across a chronic-disease cohort [14], [15]. Rehabilitation services have not previously been routed through CCHT, and the framework articulates how the platform's enrolment and care-coordinator infrastructure would absorb a motor-rehab use case. The bandwidth-tiered deployment profile (Table II) explicitly accommodates the rural-veteran broadband disparities documented by O'Shea *et al.* [13], so deployment does not depend on infrastructure that the target population does not have.

7.2. Implications for Civilian Rural Home Health

Civilian agencies such as Amedisys carry a growing rural neurorehabilitation caseload. The framework is deliberately portable: its sensing, AI, decision-support, and caregiver-interface layers do not depend on VA-specific infrastructure. The CCHT integration layer is the only VA-specific component and substitutes cleanly for an agency's existing home-health communication and EHR stack. This portability matters for two reasons. First, rural veterans receive substantial care from civilian agencies, not only from VA medical centres, and a framework deployable in both contexts is more likely to reach the population at scale. Second, civilian deployments produce evidence at a faster rate than federal procurement cycles and can de-risk eventual VA adoption.

7.3. The Therapeutic Cliff as an Engineerable Surface

The principal conceptual contribution of the framework is reframing the therapeutic cliff from a passive care-pathway artefact into an engineerable, monitorable surface. Once dose, exercise quality, and adherence are continuously measured and tied to clinical decision support, the cliff becomes a controllable variable, not an inevitability. Existing wearable-rehab work has established this technical feasibility in or adjacent to clinics [10, 11]. The framework's contribution is the deployment architecture that makes the same control feasible in a rural-veteran home.

7.4. Limitations

Three limitations are acknowledged. First, this is a design proposal, not a validated implementation. Second, the rural-veteran broadband estimates underpinning Tier 2 and Tier 3 deployment profiles are derived from cross-sectional survey data [13] and may shift as fixed-wireless and satellite (notably low-earth-orbit) coverage expands. Third, the cognitive guardrail for polytrauma and TBI is specified at framework level but requires task-level user-experience research before deployment.

7.5. Validation Pathway

Three validation studies are proposed. (i) A within-subject feasibility study at a single rural home-health agency, comparing dose, exercise-quality, and adherence metrics across a four-week pre-deployment baseline and a twelve-week framework-enabled period. (ii) A two-arm pragmatic trial within a VHA rural region, with framework-enabled CCHT versus standard CCHT for stroke and TBI patients on a one-year endpoint of independence-favouring functional outcome. (iii) A health-economic evaluation modelling per-patient cost, clinician time, and admission avoidance against a CCHT-only comparator.

7.6. Policy Levers

Three policy levers would accelerate translation. First, telerehabilitation reimbursement parity for home-health physical therapy that uses sensor-augmented documentation. Second, explicit CCHT extensions covering motor rehabilitation, supported by a defined billable service code. Third, fall-prevention reimbursement aligned with sensor-detected fall-precursor events rather than only post-fall encounters.

8. Conclusions

The therapeutic cliff is one of the most consequential and least structurally addressed gaps in current neurorehabilitation. It is steepest for rural veterans, who carry both higher disease burden and lower access to specialised care. The clinical engineering framework presented here treats the rural veteran's home as the primary rehabilitation work system and integrates wearable sensing, AI processing, clinician decision support, a caregiver interface, and Veterans Health Administration Care Coordination Home Telehealth into a single deployable architecture. The framework is grounded in SEIPS 2.0 sociotechnical principles, anchored to validated AI and wearable evidence, and explicitly designed for rural bandwidth and polytrauma cognitive constraints. Prospective feasibility, pragmatic-trial, and health-economic studies are identified as the next steps. If validated, the framework converts the therapeutic cliff from an inevitable feature of post-discharge care into an engineerable, monitorable, and recoverable clinical surface for the population least served by the current rehabilitation delivery system.

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