Hybrid Systems for Post-Stroke Upper-Limb Rehabilitation: Current Trends and Future Perspectives

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Abstract— **Hybrid systems that combine upper-limb robotics with Functional/Neuromuscular electrical stimulation (FES/NMES) aim to integrate mechanical assistance and neuromuscular activation to enhance post-stroke motor learning. A recent review on combined robot–stimulation interventions for the post-stroke upper limb reported promising outcomes, but highlighted marked heterogeneity in platforms, protocols, and outcome measures. In parallel, the Artificial Intelligence (AI)-driven rehabilitation literature identifies, as structural bottlenecks, the shortage of therapists, the difficulty of continuous monitoring, and the subjectivity of assessment, thereby motivating automated systems and data-driven evaluation. This paper proposes an AI-aware perspective on hybrid robot–FES/NMES systems for post-stroke upper-limb rehabilitation, focusing on: (i) a taxonomy of architectures and integration modalities (simultaneous vs. sequential), (ii) key control/decision gaps (triggering robustness, dose personalization, fatigue/comfort management, and clinical transferability), (iii) opportunities for integrating AI at critical points of the loop (intention perception, state estimation, stimulation adaptation, and planning/assessment). The study includes Randomized Controlled Trials (RCTs) and trial protocols that formalize combined approaches (e.g., Electromyography (EMG)-triggered co-actuation, block-wise combinations, and user-centered/wearable solutions), as well as recent contributions introducing Machine Learning (ML) models for fatigue or discomfort and EMG-based classifiers to enable more natural control.**

I. Introduction

Functional recovery of the upper limb after stroke requires intensive, repetitive, and task-oriented practice, with active patient participation to promote neuroplasticity and motor learning [1]. Rehabilitation robotics enables the delivery of reproducible and quantifiable assistance, increasing the number of repetitions and the consistency of training, while functional or neuromuscular electrical stimulation (FES/NMES) can facilitate activation of paretic muscles and enhance sensory afference during task execution [1]. The rationale behind hybrid robot–FES/NMES systems is therefore to exploit a synergy: the robot supports kinematics and reduces compensatory movements, whereas stimulation supports neuromuscular activation and volitional engagement, with the aim of amplifying training effectiveness compared with either component alone [1].

A recent systematic review focused on combined interventions for the post-stroke upper limb identified nine studies including 359 participants, but also highlighted limited comparability due to variability in platforms, stimulation parameters, timing integration, and clinical outcomes [1]. In parallel, a stream of reviews on AI-driven systems for post-stroke rehabilitation and assessment emphasizes that the shortage of therapists makes rehabilitation services costly and often insufficient, and that clinical evaluation can be subjective and poorly scalable, thereby motivating the development of automated systems and data-driven metrics [2]. In that work, the authors adopt the PRISMA approach qualitatively and quantitatively to analyze robot-assisted rehabilitation, Virtual Reality (VR)-based rehabilitation, and automated assessment methods; they report high agreement between automated methods and therapists on datasets such as KIMORE and UI-PRMD, and deep-learning performance on skeleton data with Root Mean Square Error (RMSE) values down to 0.55 [2]. Recent advances in digital-twin-based robotic sensing further support this AI-aware perspective. For instance, the work in [3] proposes an AI-assisted Electronic Digital Twin (EDT) for capacitive pressure sensors controlling robotic gripping, using CNN-based classification of pressure-related signals to support robotic hand control. Although this contribution is not specific to post-stroke robot–FES/NMES rehabilitation, it provides a useful methodological reference for sensor-level simulation, tactile sensing, and preclinical validation of robotic hand subsystems that could be integrated into future hybrid rehabilitation architectures.

Starting from these findings, in this work we propose an AI-aware taxonomy and an AI-integration roadmap for hybrid robot–FES/NMES systems for post-stroke upper-limb rehabilitation. The goal is not only to demonstrate that the robot–stimulation combination works, but to design adaptive, robust, and clinically transferable systems capable of: (i) recognizing intention and task phase [4], [5]; (ii) modulating stimulation dose as a function of patient state [5], [6], [7]; (iii) handling fatigue/comfort/safety constraints [6], [7] and (iv) supporting objective assessment and therapeutic progression [8]. The review is structured leveraging the main academic digital libraries (i.e., Scopus, IEEE Xplore, and PubMed), with different refined queries, and only focusing on publications from 2020 onwards (see the flow diagram in Fig. 1 for details), leading to the identification of 25 articles.

II. Taxonomy of Hybrid Robot-FES/NMES System

A. Robotic Architectures and Functional Targets

Regarding platforms, therapeutic robots for the upper limb are commonly classified into end-effector and exoskeletal

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systems, with different implications in terms of kinematic constraints, joint alignment, and human–machine interaction modalities [1]. Functional targets span both proximal movements (shoulder–elbow) and distal movements (wrist–fingers/hand), with systems designed to deliver repetitive, guided, and measurable training [9], [10].

At the proximal segment, the work in [11] investigated whether non-triggered NMES could increase the effectiveness of robotic shoulder and elbow training in subacute patients, including 30 patients randomized to robot-only vs. robot + stimulation. In the same study, NMES is described as a potential enhancer of robotic rehabilitation, with shoulder Range of Motion (ROM) measures (flexion/abduction) and Fugl-Meyer assessed pre/post treatment.

In the distal domain, the contribution in [9] adopts a Randomized Controlled Trials (RCT) to compare EMG-driven robotic hand training with and without NMES, enrolling 30 chronic patients and prescribing 20 sessions with a 3-month follow-up.

A relevant line of architecture combines robotics and FES/NMES via physiological triggering, a single-blind RCT recruited 72 patients and delivered a 9-week training program, three times per week, comparing an experimental group performing task-oriented exercises assisted by a robotic system with EMG-triggered FES against a control group [4].

Another hybrid strategy, sequential/modular type, evaluated an approach in which task-oriented Myo-electrically Controlled Functional Electrical Stimulation (MeCFES) is applied and subsequently combined with robotic therapy. The study in [5] recruited 18 subjects, and the protocol included 20 sessions of 45 minutes, with Fugl-Meyer Assessment-Upper Extremity (FMA-UE) as the primary outcome. To enable deployment in realistic and potentially home-based scenarios, a user-centered 3D-printed hybrid orthosis, was developed and clinically evaluated within a prospective open-label feasibility study featuring eight-week sessions and home use. The authors report that participants learned to use NuroSleeve in Activity of Daily Living (ADL), and that the device met feasibility and safety objectives [12].

Finally, in [13] is proposed an architecture termed as exoneuromusculoskeleton, combining NMES, soft actuation (pneumatic muscle), and exoskeletal elements. Feasibility was assessed in chronic stroke patients (n=10), and the authors report improvements after a 20-session training program and increased extension ROM when both mechanical torque and NMES are provided.

B. *Robot–Stimulation Integration Modalities: Simultaneous vs. Sequential*

In hybrid systems, integration can be conceptually mapped onto two main modalities: simultaneous (co-actuation within the same motor act) or consecutive/sequential (components delivered in distinct blocks) [1].

In simultaneous modality, robotics and stimulation are coupled in real time to support both kinematics and neuromuscular activation during task execution, typically through assist-as-needed logics and/or physiological triggering [4], [5], [9], [14]. A tight coupling example is the integration of EMG-triggered FES with task-oriented robotic training in a single-blind RCT on 72 patients with a 9-week intervention [4]. Another example of in-loop co-actuation is EMG-driven robotic hand training combined with NMES, experimentally compared against the same robotic training without stimulation in an RCT enrolling 30 chronic patients over 20 sessions [9]. A simultaneous variant less dependent on stable voluntary command is the use of non-triggered NMES during robotic shoulder–elbow training in 30 subacute patients [11].

In the sequential/consecutive modality, by contrast, FES/NMES and robotics are applied in separate phases (within the same session or across blocks) to reduce control complexity and standardize the protocol [1], [5]. The MeCFES + robot therapy study describes a protocol in which a task-oriented MeCFES session is immediately followed by robot therapy, delivered as 20 sessions of 45 minutes, with clinical outcomes (FMA-UE) as the primary endpoint [5]. A block-wise combination is also described in an RCT on 61 subacute patients randomized into three groups, where the robotic therapy combined with electromyography-triggered neuromuscular electrical stimulation (RT–ENMES) group receives 20 minutes of robotics + 20 minutes of ENMES, while other groups receive 40 minutes of a single component; the authors report significant improvements, and greater gains in the combined group, on FMA-UE, Action Research Arm Test (ARAT), and Motor-Evoked Potential (MEP) [10]. The formalization of these strategies is further supported by recent trial protocols: a Trials protocol describes a three-arm single-blind RCT (n=60) comparing robot+FES versus robot-only and conventional therapy [15]. In [16] a protocol describes an RCT (n=162) to evaluate FES, Robot-Assisted Therapy (RAT), and FES-RAT programs, with emphasis on synergy-based FES and reach-to-grasp retraining.

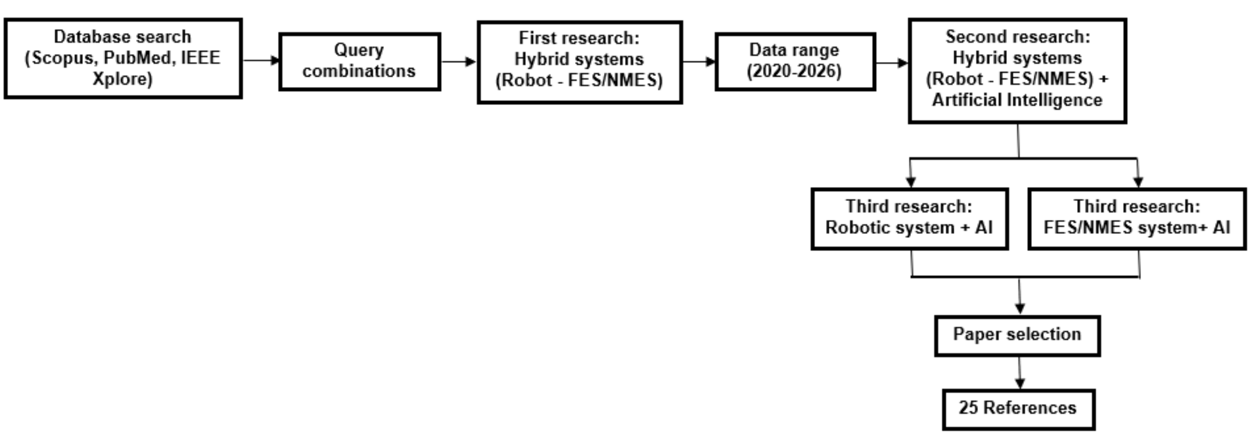

Figure 1. Flow diagram of the adopted state-of-art research methodology.

TABLE I. EMERGING PROBLEMS AND CHALLENGES FROM THE LITERATURE REVIEW.

Problem	Impact on the system	Technical reasons	Example	AI-based mitigation strategy
P1. Triggering / intention not robust	Late or incorrect stimulation; loss of voluntariness; compensation; poor repeatability	Noisy EMG/cross-talk; electrode drift; cross-session variability; pipeline latency	EMG-triggered control in RCTs and EMG-driven training [3], [8]; EMG classification with ANN [17]; motion estimation with PNN [18]	Motor-intent and motion-estimation module. ANN-based EMG classifiers can detect movement intention and select the corresponding orthosis/FES action [17], while PNN-based motion estimation can drive both robotic assistance and FES from EMG signals [18]. This module could improve triggering robustness by estimating the movement state before activating stimulation and robotic assistance.
P2. Insufficient FES/NMES dose customization	Over/under-stimulation; incomplete movement; low effectiveness; low tolerance	Muscle–stimulation nonlinearities; inter-individual differences; lack of state-aware closed-loop control	Need for standardization highlighted in the review [1]; multi-arm trial protocols to compare dose/strategies [14], [15]; ML-aided FES (LSTM + regression) [21]	Adaptive FES/NMES dose-personalization module. EMG-based ML can personalize stimulation parameters by combining LSTM/boosting classification and regression-based FES signal adjustment [21] with fatigue-aware SVM adaptation of NMES amplitude, pulse width and frequency [6]. Building on these contributions, performance-driven adaptive control principles, such as RL-based assist-as-needed strategies [13], could be extended to jointly personalize robotic assistance and FES/NMES dose.
P3. Fatigability and performance decay	Decreased quality of movement; reduced adherence; risk of adverse effects.	Fatigue accumulation; EMG fluctuations; compensatory strategies; lack of state estimation	SVM for continuous fatigue detection and stimulation adaptation [6]	Fatigue-detection and closed-loop stimulation-adaptation module. SVM-based fatigue estimation from EMG time/frequency features can dynamically adapt NMES amplitude, pulse width and frequency in hybrid robot–NMES systems [6], reducing overstimulation and discomfort. This module could also support rest periods or assistance redistribution when severe fatigue is detected.
P4. Comfort / pain as an unmodeled constraint	Drop-out; low acceptability; limitation of therapeutic intensity	Variable pain threshold; electrode placement; skin sensitivity	Fuzzy pain detection and stimulation regulation in an upper-limb exoskeleton [5]; user-centered/wearable settings [11]	Comfort/pain safety-constraint module. Fuzzy-logic pain detection can use EMG features, range of motion, joint/resistive torque, and therapist-supervised thresholds to adapt stimulation and exoskeleton parameters to patient-specific tolerance [5]. This module would transform comfort and pain from qualitative usability concerns into explicit safety constraints within the closed-loop controller.
P5. Heterogeneity of protocols and incomplete reporting	Difficulty in comparison; reduced replicability	Unreported FES parameters; unspecified synchronization; heterogeneous outcomes	Review including 9 studies / 359 participants and reporting heterogeneity [1]	AI-ready protocol standardization and data-quality module. A rule-based data-quality layer could check the reporting of key hybrid robot–FES/NMES variables, such as stimulation parameters, synchronization, latency, data acquisition, and adaptive-control architecture [1], [5], [6]. Based on CDSS-oriented data management [7], it could generate a reporting checklist and protocol-completeness score to improve reproducibility and comparability.
P6. Clinical Evidence limited / transferability	Limited Generalizability of Benefits; Laboratory-to-Clinical Gap	Small samples; heterogeneous inclusion criteria; limited follow-up	RCTs and pilot studies with heterogeneous designs [3], [4], [8], [9]; RCT protocols [14], [15]	Patient-stratification and response-prediction module. ML models can predict rehabilitation outcomes (e.g. FMA and FAT scores) from clinical/demographic data, robotic kinematics, and sEMG–kinematic features [7], [23], [24]. Extended with stimulation-response variables, this module could support patient stratification and personalized selection of hybrid robot–FES/NMES strategies.
P7. Lack of objective and scalable assessment	Challenging Optimization/Decision-Making; Subjective Outcomes	Discrete clinical scales; manual observation; limited granularity	AI-driven review on automated assessment and therapist agreement [2]	Automated assessment and decision-support module. ML-based assessment models can transform sensor, kinematic, interaction-force, task-score, and sEMG data into objective performance scores, outcome predictions, and exercise-parameter recommendations [2], [7], [24]. Movement-quality metrics such as accuracy, stability, and smoothness could support progression decisions in hybrid robot–FES/NMES systems [18].

C. *Sensors, Triggering, and the Role of Volitional Control*

Many systems rely on EMG to enable active participation and/or to trigger stimulation, with the goal of aligning electrical assistance with motor intent [4], [9], [17].

The relevance of integrating EMG signals is also highlighted in an engineering study proposing the control of a hybrid orthosis via a data-driven Artificial Neural Network (ANN) classifier operating on electromyography signals, with the aim of selecting movement intention through EMG classification [18]. In [19], an EMG-driven hybrid system is described based on motion estimation via a probabilistic neural network, where EMG drives the combined control of robot and FES, and training effects are assessed on non-dominant wrist "pointing" tasks using accuracy, stability, and smoothness metrics. These approaches suggest that, beyond a simple "trigger," AI can act as a perception module capable of handling variability and making control more natural.

III. Gaps And Challenges For Traslation

By analyzing the literature review on hybrid systems for post-stroke upper-limb rehabilitation, recurring criticalities emerge that hinder transferability and the standardization of findings. These problems are summarized in Table I in terms of their impact on the control/decision loop, technical causes and examples. In particular, in [1] a systematic review on combined systems is proposed, reporting heterogeneity in platforms, stimulation parameters, integration timing, and outcomes, making it difficult to compare protocols and to isolate the mechanisms driving clinical effectiveness. In parallel, the review presented in [2], analyzes AI-driven systems for post-stroke rehabilitation and assessment, highlighting that therapist shortages and the limited scalability of clinical evaluation motivate the adoption of automated pipelines and data-driven metrics, which become particularly relevant in hybrid systems where the dose of stimulation and assistance should be adapted to the individual patient.

IV. Artificial Intelligence In Hybrid Systems

In the field of hybrid systems, the key question is not merely whether to use AI, but where to place it within the control loop (perception → decision → actuation → evaluation) to improve robustness, personalization, and safety without excessively increasing system complexity and clinical burden [5], [7], [19].

The literature review on hybrid systems highlights that in simultaneous co-actuation, real-time intention and state estimation are required, whereas in sequential architectures protocol standardization and scheduling/parameterization decisions across blocks become central [1].

The AI-driven review in stroke rehabilitation, although not specifically focused on robot + stimulation hybrids, supports the idea that AI modules for assistance, assessment, and decision support are transferable [2]. More in details, the transferability of AI modules to a hybrid system is maximized when the model inputs and outputs coincide with quantities already measured or controlled in the robot–FES/NMES architecture, such as EMG signals, kinematic/force variables, stimulation parameters, performance indices, and clinical scales [7], [20]. In this scenario, AI does not introduce additional sensors or workflows; rather, it is embedded as an inference and decision layer between perception and actuation, coherently linking the two assistance channels (mechanical and electrical). This enables a shift beyond open-loop integrations or static rule-based schemes toward data-driven, closed-loop strategies capable of adapting assistance and stimulation in real time to the patient's state and the task, thereby improving robustness and personalization [6], [7], [18].

The next subsections discuss AI modules validated in rehabilitation robotics or in standalone FES/NMES, yet directly reusable within a hybrid system.

A. *Motor Intent Perception*

In hybrid systems, the effectiveness of triggered strategies (e.g., EMG-triggered FES) depends critically on the quality of intent estimation, because more reliable decoding reduces false triggers and improves synchronization between electrical activation and the movement phase [4]. From this standpoint, adopting EMG-based data-driven models to command a hybrid orthosis already represents a mature paradigm. The intelligent component can make the translation of inherently noisy myoelectric signals into control commands more robust and repeatable, enabling more natural and potentially safer interactions [18], [19]. Consistently, an AI-enhanced hybrid system integrating robotics and NMES explicitly includes a monitoring/estimation layer to support real-time adaptation, suggesting that AI can be placed upstream of actuation to stabilize the loop and enable more consistent control decisions [7].

On the transferable robot + AI side, an EMG-driven robotic hand integrating AI/ML modules for EMG interpretation provides a direct example of how intent estimation can drive assistance/actuation in distal tasks, with immediate implications for hybrids combining robotic hand training and NMES [17]. Moreover, motion/intent estimation approaches based on probabilistic neural networks can be viewed as additional enablers within a hybrid system, a more reliable estimate of motor state can inform both stimulation timing (when to stimulate) and the allocation of mechanical assistance (how much to assist) throughout task execution [19].

B. *Decision/Adaptation (Assist-as-Needed, Tuning, Personalization)*

Once intent has been estimated, AI can be embedded in the loop as a decision policy that modulates robotic parameters (e.g., impedance, assistance level, task difficulty) and/or FES/NMES parameters (e.g., amplitude, duty cycle, timing) to maximize engagement and performance while preserving comfort and safety [6], [7], [14].

EMG-triggered systems aim to couple actuation to voluntary effort, reinforcing active participation and reducing "passive" assistance; conversely, sequential architectures (e.g., MeCFES followed by robot therapy) make explicit a scheduling and load-progression problem across therapeutic blocks, where dose, ordering, and advancement criteria must be selected as a function of patient response [4], [5].

At this point in the loop, robot + AI studies are particularly valuable as transferable modules. In particular, reinforcement-learning based strategies for personalized assistance in robot-assisted reaching illustrate how to learn a policy that dynamically adjusts the level of help based on user performance, maximizing indicators such as engagement and learning/retention. This approach is directly reusable in hybrid systems, where the policy must also allocate contribution between mechanical support and stimulation [14], [21].

In parallel, decision-support approaches based on sequential models (e.g., Long Short-Term Memory (LSTM)) to recommend training parameters and difficulty in accordance with therapist choices provide an operational template to standardize and personalize settings: in a robot + FES/NMES arm, the same principle can be extended by incorporating stimulation variables and tolerability, enabling systematic governance of both robotic progression and electrical-dose progression [20].

C. Physiological State Estimation and Constraints (Fatigue/Comfort/Safety) → Stimulation Control

AI can be positioned within the loop as an observer of the human state (fatigue, pain/discomfort, risk), imposing constraints on actuation and preventing drop-out or over-stimulation [7]. For instance, decision modules can be introduced to manage discomfort via fuzzy-logic–based pain detection in an exoskeleton context, which is conceptually aligned with safety-aware stimulation control [6].

Even more aligned with the hybrid system + AI theme is the AI-enhanced system combining a dual-arm robot with NMES and integrating a fatigue-estimation module (e.g., via SVM) to dynamically adapt stimulation parameters, making AI an integral part of the closed-loop neuromodulation during exercise [7].

This paradigm is further supported by transferable FES/NMES + AI contributions, where machine-learning models for stimulation-signal generation/optimization (e.g., pipelines based on LSTM/boosting and regression) demonstrate the transition from static settings to personalized, adaptive stimulation, which is an aspect that is particularly critical when stimulation operates in-loop, while robotic therapy imposes kinematic constraints and performance objectives [22].

In parallel, in the mechanical assistance domain, advanced control schemes for wearable exoskeletons (e.g., adaptive/robust controllers with disturbance observers) provide a useful reference to discuss robustness and interaction safety [23]. In a hybrid system, such strategies can coexist with AI modules enforcing constraints on stimulation (comfort/fatigue) and enabling coordinated management of both actuators within clinically sustainable safety envelopes [6], [7].

D. Outcome prediction / stratification / data-driven assessment

An additional insertion point for AI is downstream of actuation, as an assessment and prediction layer that estimates expected recovery, treatment response, and progression trajectory, thereby supporting high-level decisions (selection of modality: robot-only, FES-only, simultaneous hybrid, or sequential hybrid) and longitudinal dose personalization [20]. In this direction, studies integrating machine learning with data derived from rehabilitation robotics to predict outcomes or support clinical decisions are particularly relevant, as they introduce the concept of a “supervisor” that updates protocols and parameters based on kinematic performance and clinical measures [25], [26].

A concrete and transferable example is a Clinical Decision Support System (CDSS) that uses features extracted from robotic sessions to predict outcomes and recommend exercise parameters, reporting recommendation performance through metrics such as accuracy and F1-score [20]. In a hybrid system, the same framework can be extended by incorporating stimulation-specific features (delivered dose, patterns, tolerability/discomfort, fatigue indicators), yielding a more comprehensive decision-support layer capable of jointly governing robotic and stimulation progression under a truly personalized paradigm [6], [7], [20], [22].

V. Discussion

The work in [1] highlights heterogeneity and difficulties in comparing studies, indicating the need for comprehensive reporting of parameters and protocols. More in detail, as summarized in Table I, the main issues emerging from the literature include non-robust triggering/intention detection, insufficient FES/NMES dose customization, fatigability with consequent performance decay, comfort/pain treated as an unmodeled constraint, high protocol heterogeneity and incomplete reporting, limited clinical evidence and transferability, and the lack of objective, scalable assessment frameworks.

To improve comparability and replicability, it is advisable to always report target muscles and electrode placement, FES/NMES parameters (amplitude, pulse width, frequency, duty cycle), robot stimulation synchronization (simultaneous vs. sequential), triggering logic and failure handling (e.g., absent EMG, noise), and end to end loop latency when an AI module is present [1], [7], [10].

The AI models proposed in the relevant literature, that is, ANN for intention [18], Probabilistic Neural Network (PNN) for motion estimation [19], Support Vector Machine (SVM) for fatigue [7], fuzzy logic for pain [6] and LSTM/regression for stimulation [22], indicate feasibility, but translation requires robust and comparable validation.

In this direction, the AI-driven review emphasizes the need for reliable automated systems and assessment consistent with clinical standards, supporting the use of datasets and quantitative metrics to evaluate agreement with therapists [2].

For hybrid systems this implies cross-session testing (electrode/condition variability), noise-sensitivity analyses, and conservative fallback strategies when uncertainty increases [7].

The presence of a fuzzy pain-detection module to adapt stimulation and an SVM module to detect fatigue and adjust parameters suggests that comfort and physiological load should become explicit constraints [25], [26].

VI. Conclusion

This work analyzes the state of the art of hybrid systems for post-stroke upper-limb rehabilitation, with a specific focus on where to embed AI within the control loop to enable more adaptive and clinically transferable architectures. The literature shows a solid physiological and engineering rationale but also marked heterogeneity in platforms (end-effector/exoskeleton/orthosis), protocols, and integration logics (simultaneous vs. sequential), which makes it difficult to compare effects and converge toward shared clinical standards. At the same time, the contribution includes concrete examples of trials and experimental protocols and introduces AI-ready modules for intention estimation (ANN/PNN), fatigue monitoring (SVM), comfort management (fuzzy logic), and stimulation personalization (LSTM + regression), indicating that the technological building blocks for a closed-loop system are already available.

Building on the main gaps highlighted by the literature, our future work will investigate patient performance after upper-limb rehabilitation with existing hybrid robot–FES/NMES systems by leveraging sensor fusion (e.g., surface EMG, inertial and/or tactile sensing, complementary kinematic signals) coupled with AI-based models, such as for intention detection, state estimation, and outcome prediction. We also plan to investigate how other hybrid rehabilitation architectures can be applied for post-stroke robot–FES/NMES rehabilitation. In parallel, we aim to integrate these multimodal signals with baseline clinical databases (e.g., age, sex, medical history, prior therapies and medications) to enable stratified analyses and the development of data-driven decision-support tools, contributing to clinical decision-making.

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