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Human-AI Cooperation in Healthcare and Rehabilitation

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Abstract

Rehabilitation after injury or to manage chronic health conditions requires continuous reassessment and intervention across time scales ranging from seconds to months. Advances in sensors and data collection, coupled with new technology to administer interventions, create numerous possibilities—including at-home care. The increased capabilities enable automated analysis and control using artificial intelligence (AI). In this essay, we analyze the need, the potential and the requirements for an intense and enduring physical human-AI cooperation framework, i.e., a symbiosis, where both AI and humans contribute to realize improved solutions. The focus is the development of knowledge and expertise to realize a new generation of AI-enabled therapy for the next decades. With an aging population, prevalence of stroke and chronic diseases, there is a demand for more efficient and effective rehabilitation powered by human-AI cooperation, especially in cases that enable remote participation in areas with limited access. This essay analyzes how the potential for advances in human-AI cooperation can impact rehabilitation in Delaware.

Introduction

This paper discusses the state-of-the-art and the potential, both near-term and long-term, to improve therapy and rehabilitation through human-AI cooperation, along with initial plans as developed by an interdisciplinary team of researchers. The use case of personalized rehabilitation and healthcare is intrinsically challenging, as it requires decision making with incomplete, multimodal data at several time scales about a patient's health informed by experience and knowledge of current evidence. In particular, stroke rehabilitation involves efficiently gathering information through diverse methods[1] on motor-sensory deficits, given the patient's previous abilities, to outline exercises and assistive robotics, which will most effectively re-establish lost abilities—in an environment limited by possible impairments in speech and cognition.[2] Both the patient's health and the clinician's understanding of the patient's current health and goal state change through multiple sessions due to the treatment and unobservable factors, with the vast majority of time being outside of clinical observation. In this context, advances in artificial intelligence technologies can enable the seamless analysis and integration of static and dynamic patient data collected by multimodal sensors within and outside of the clinic.[3–5] This includes real-time closed-loop sensing with robotic,[6] computer, and machine interfaces for patient sensory stimulation and monitoring, expert-guided (human-in-the-loop) contextualization of patients based on relevant information into strata for optimized treatment, and personalized AI-enabled communication interfaces for expanding patient-clinician dialogue for patient support and engaging in out-of-clinic exercises and assessment.

Sensorimotor disabilities resulting from neurological disorders or injuries are a pressing challenge[7] as rehabilitation is both financially burdensome and labor-intensive. Prevailing rehabilitation practices lack customization. The goal is to harness technological advancements in robotics and sensing to tailor treatment to each patient's characteristics by developing AI models proficient in leveraging limited patient-specific data and existing knowledge to project potential functional outcomes of interventions into the future. The data sources encompass patient interactions with clinicians, robotic mechanisms in clinical environments, and wearable sensors capturing patient activity in daily life settings.

Challenges and Potential

Although progress has been made based on emerging AI techniques, current AI cannot yet truly act as a partner in decision making due to limitations in its foundations and the realities of the use case. For example, machine learning approaches for data processing do not provide conceptual grounding to reason about the information content of heterogeneous data, which is necessary to communicate uncertainty and optimize the gathering of additional data. AI must consider a patient's health as a partially observable state and clinicians need to be able to specify goals and constraints directly. The validity and relevance of data and knowledge are continually evolving at multiple scales beyond the dynamics of individual patients; new sensors or treatments will become available while others become obsolete; new evidence will lead to changes in standards of care; and the population of patients will change. Modeling and/or optimizing treatment in such nonlinear, time-evolving systems is a challenge. Even with improved sensing, it is not trivial to extract meaningful information from data to identify the causal relationships of variables of interest in a dynamic environment. Additionally, there is no blueprint on how to divide the roles between human experts and AI to maximize human-AI performance for clinical decision making.

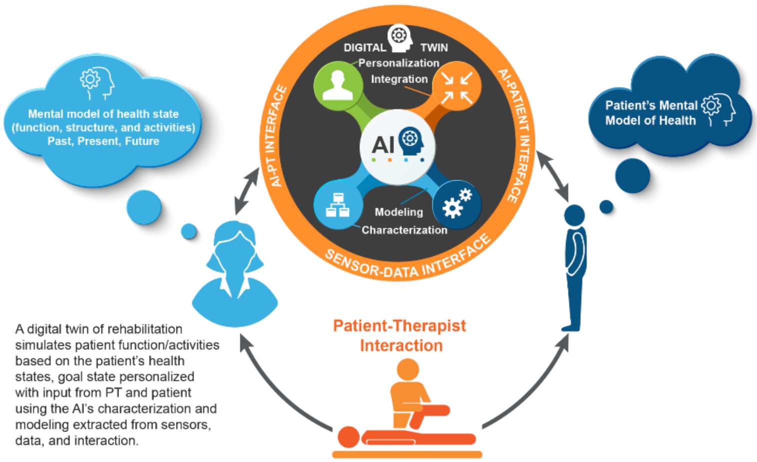
AI for rehabilitation has unique specialized algorithms and ethical implications. It requires creating a research nexus between AI researchers, physical therapy researchers, community stakeholders, and industry partners ranging from computing hardware/software and medical equipment manufacturers to healthcare providers. Initially, pilot projects operating at different scales are needed to validate developments in real-world settings and identify new challenges and solutions as foundational contributions are realized. Patient and clinician/physical therapist feedback should be sought during *co-design* to assess how user-friendly and efficient these AI-assisted systems are in a real-world therapeutic context. There is also a need to connect and educate a spectrum of people from AI researchers to health-care practitioners.

In current rehabilitation research, models of human physiology and psychology blend mechanistic and empirical models at different scales of accuracy. Yet, even with this imperfect understanding using limited data, clinicians characterize subjects and personalize treatment, so their role in guiding the final architecture choices is fundamental.[8] At the same time, clinicians stand to benefit from AI's computational power to integrate massive and diverse information in data repositories, from natural language to information-rich signals from video and sensors and to identify subtle patterns in massive quantitative data. AI is also advantageous because its continuous operation does not lead to degradation of performance due to the stress or exhaustion as happens with humans. However, novel human-AI systems capable of leveraging the intelligence of both the human and AI in cooperative feedback through *grounded concepts* is needed.

In rehabilitation and healthcare, AI operation must be specific to the characteristics of an individual, which evolve at a variety of timescales. The AI systems must be *trustworthy*, *instructable* and *aligned* with the patient's goals as supervised by clinicians. The rehabilitation of sensorimotor disabilities through physical therapy involves human motor learning, which relies on the nervous system's ability to integrate sensory information, control movement, and plasticity, governed by an individual's intrinsic reward. These characteristics are desired in AI systems. Thus, an improved understanding of natural learning is synergistic with advances in human-AI cooperation.

Vision for AI-enabled Human-AI Cooperation. We imagine an AI-enabled system for human-AI cooperation (Figure 1) that can dialogue with the human expert to inform if a particular intervention could maximize the rehabilitation goals for a given patient. This will improve the outcomes through the clinician's (therapist's) enhanced abilities to make sense of a variety of sensors and data and the patients' ability to interact with AI-enabled devices to support their participation in therapy. In addition to sensors and data, the AI system can directly use instructions and feedback from users (both therapists and patients) and monitor (with informed consent) the patient and patient-therapist interaction via multiple modalities. Even with these data sources, the AI's information may be limited compared to the users. To ensure that the therapist's mental model of the patient aligns with the AI's characterization, we propose to use a digital twin and simulation environment to provide an avatar in a virtual embodiment for exploring and displaying structural and functional aspects of the AI's model of a patient.[9] This can serve multiple purposes including providing a patient with a guide for exercises and visualization of future health states.

Figure 1. Illustration of the Human-AI Cooperation in the Context of Rehabilitation.



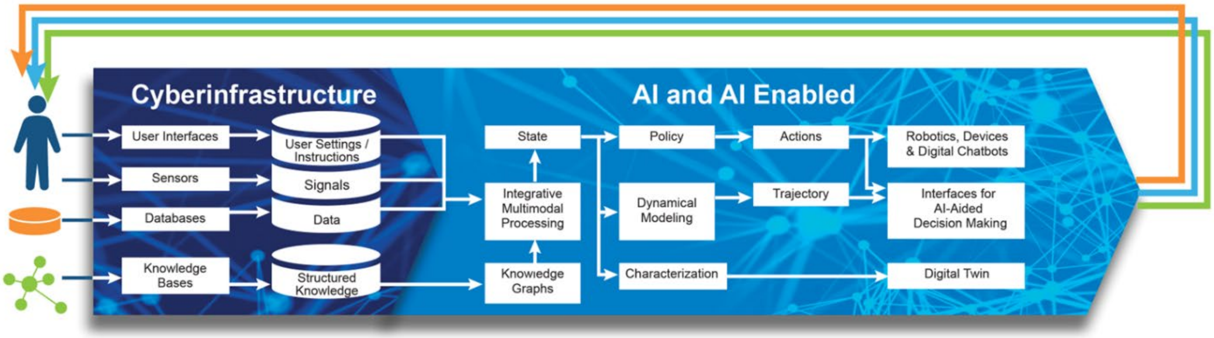
A digital twin of rehabilitation simulates patient function/activities based on the patient's health states, goal state personalized with input from PT and patient using the AI's characterization and modeling extracted from sensors, data, and interaction.

This requires modeling complex, stochastic, and dynamic processes from heterogeneous data at multiple scales and for estimating and adapting optimal policies for specific individuals, contexts, or strata of human populations in the presence of new information and direct human instruction. There is a need for cross-cutting approaches for extracting relevant information from data, fusing real and simulated data—while robustly handling distribution shifts, and creating accessible and multimodal human-AI interfaces that ensure alignment of AI operation with user intent through direct instruction and goal specification grounded in human language (verbal and non-verbal forms, data exemplars, and other knowledge representations). The grounded interfaces will also allow AI explanations of model predictions and decision-making, ensuring alignment for the human-AI cooperation during both model adaptation and real-time operation. AI-enabled robotic agents can be used for rehabilitation and assistance, including applications in rehabilitation exercise robots, prosthetics, and orthotics. More comprehensively, human-AI cooperation requires ethical framework and neuroscientific perspectives of, including studies of the neural correlates of trust, error, and reward, using brain-computer interfaces.

We envision AI as a tool to make sense of the revolutionary technical capabilities that every day extend the quantitative assessment of physical health both inside and outside of the clinic to provide real-time interaction for analysis. Using the increased sensing, we envision AI empowering adaptive mechanisms in rehabilitation (including robotic assistance and functional stimulation) to provide personalized and effective interventions for patients. In particular, robot-assisted interventions could be customized based on the predictive abilities of the AI models. This approach allows the system to determine the most suitable intervention for each patient based on their unique functional needs. Similarly, using advances in natural language interfaces and augmented/virtual reality, AI-based virtual interactions can provide virtual coaching and feedback that is critical for optimal rehabilitation outcomes which require specific activity and guided, individualized exercises outside of the clinical setting. The physical therapist or clinician and the patient would use the *digital twin* to review the model's proposed approach, refine it by instruction, and the AI would personalize it to the patient and clinician through *preference elicitation*. At home, the digital twin, wearable sensors, and natural language interfaces would enable an interactive and adaptable session. This type of personalized care can enhance compliance with exercise instruction and improve outcomes.[10] The physical therapist can interact with the AI to modify the exercises, prompts, and instructions at the next clinic visit. Such human-in-the-loop optimization can result in more responsive and efficient care that represents a critical next step in rehabilitation and healthcare that has been sorely lacking.

Our description of a system for human-AI cooperation (Figure 2) is meant to convey the overall information flow and processing and interfaces involved. Loops will allow human-AI co-exploration, policy improvement, user preference elicitation, and AI-guided data exploration.

Figure 2. Information Flow in an AI System for Human-AI Cooperation



Potential Milestones for Human-AI Cooperation in Rehabilitation

Goal 1. Provide rapid analysis of information-rich synchronized multimodal measurements (video, motion and force capture, brain activity) of cognitive state, muscle activity, and sensory-motor feedback to help characterize a patient's state and progress in recovery towards goals. This requires the following:

- Integration of measurements of varying fidelity outside of the clinic with those inside the clinic.
- Identification of relevant patterns in multimodal data—both static patterns and longitudinal trends.
- Instantiation of digital twins for interactive exploration and simulation of patient activity.
- Characterization of a patient as being of a particular group or strata relevant for treatment.
- Retrieval of relevant cross-sectional data and knowledge to support statistical reasoning.
- Uncertainty quantification of predictions to inform subsequent measurements.

Goal 2. Model the longitudinal dynamics of patient health trajectories to aid in diagnosis and treatment. This requires the following:

- Simulation of patient rehabilitation with a digital twin to explore how function and activities are predicted to be impacted through different treatment to aid decision making.
- Progression tracking with automatically updating data products and early detection of changes.
- Expert-in-the-loop algorithms for optimizing patient-specific policies reactive to real-time data.
- Calibration of closed-loop systems (robotics and medical devices) for AI-enabled therapy.

These milestones are ambitious and go well beyond the current state of practice. Sensors outside of the clinic will support wider access via telehealth and interactive and aligned AI-enabled systems will support remote therapy outside of visits. Long term, a universal model for patient health/rehabilitation trajectories at scale grounded in knowledge-based concepts will enable human-AI cooperation for generating hypotheses and insights from studies that currently are not comparable due to differences in interventions and data collection methods. The use of AI will provide a major advance in our ability to interpret data efficiently and precisely, to gain insight on the underlying deficits and predict progress through rehabilitation, and to achieve AI-aided clinical decision-making.

Key Components

Integration

Grounded AI requires an ability to make sense of varied data. Most clinical contexts, and indeed human decision making, naturally involve multimodal data. Consequently, the integration of diverse multimodal data streams is critical for advancing our understanding and computational abilities, particularly in the context of enhancing human-AI collaboration. Multimodal data, which may include video, motion capture, audio, text, streaming sensor outputs, and human-provided instructions, presents unique challenges due to its heterogeneous nature. These data types exist across various spatiotemporal scales. Frequently the sensory data is incomplete or imprecise, requiring sophisticated frameworks that can not only handle this diversity but also leverage it to empower human decision-making alongside AI systems.

There is a need for a framework for the effective integration of such multimodal information, facilitating abstracted learning and reasoning that operate across multiple scales. This is essential for grounding complex data with inherent “missingness”, extracting meaningful information from them in a manner that supports robust learning and inference by both humans and AI systems. Critical capabilities for reliable human-AI decision-making in unpredictable environments include uncertainty quantification and bounds on performance in the presence of changing data distributions.

Data Sources

The top-ranked University of Delaware (UD) Physical Therapy program can provide data from multi-site randomized clinical trials in rehabilitation. The program has generated large and rich research data, including human motion capture, force and muscle activity, and electronic health record (EHR), to address complex problems of activity and participation.[1,11–15] Another data source is deidentified multimodal data of primary care clinical encounters collected by Penn Engineering and Medicine, including video, audio, transcripts, EHR, and audit logs.[16] The data provides an unprecedented view in an ML-ready format while preserving patient privacy. The long-term goal is to enable in-clinic AI analysis of a patient's data to provide context of a patient’s physical, cognitive, and emotional health state, support real-time clinical decision-making, alert clinicians to relevant patterns and changes, and improve the clinical processes to achieve a higher standard of care.

Grounded AI for human-AI dialogue and explanations. Next-generation AI must be able to receive direct instructions from users in various modalities, and it must be able to provide explanations that are both understandable to users and faithful to the AI reasoning processes.[17,18] AI-human interfaces should be bi-directional: in the human-to-AI direction, instructions and other interactions will form the context of the state representation that is used in the AI’s subsequent predictions; and in the AI-to-human direction, the model needs to be able to provide explanations of its predictions or outputs.[19] The first direction requires understanding the best way to represent these instructions as part of the state, objective, or constraints on the policies or actions. The second direction builds on our work on explainable AI.[19] Instructable multimodal language models can provide explanations of their predictions, essential in healthcare and other safety critical applications. In particular, large language models (LLMs) trained on extremely large bodies of text and dialogues have made interactions between machines and humans seem deceptively solved. LLMs fine-tuned on instructions have demonstrated the ability to follow instructions and engage in open-ended dialogue. Building on this, ChatGPT and other dialogue systems[20] leverage instruction fine tuning on a large corpus of conversational data to enable engaging in natural back-and-forth conversations while following instructions and context. But human interaction is not just limited to text; it is holistic and multimodal and may need to be personalized. Often, humans interact via gestures and body language as well as by conversational common ground that includes shared visual referents. Large vision-language models (LVLMs) that integrate visual inputs along with text provide an opportunity to study communication at the intersection of vision and text. Can these techniques for creating a shared representation between language and vision be extended to other modalities like human poses[21] gathered from sensor data? For instance, could an AI agent helping a patient with their physical therapy exercises be able to view the patient's motions and give instructions on what other motions to make using understandable language?

To deliver multimodal instructability and faithful explanations that mitigate hallucinations, we envision novel approaches for verbally describing relationships and patterns in sensor data, visualizations, knowledge graphs and other media, and then training networks to embed these in shared embedding spaces. One potential approach is to augment existing non-language data with language descriptions using LLMs and LVLMs. We propose to extend our framework for synthetic data generation and multimodal model training via complex prompting workflows.[22] We envision this synthetic data may take the form of language that describes data signals, including producing chain-of-thought-style reasoning[23] and instruction-style data,[24,25] and then training multimodal generative models on this data. By building frameworks for synthetic data generation and multimodal model training, we will be able to augment data collected in other portions of our AI2HAI program to create specialized AI systems built for our use cases including physical therapy, and that will provide adaptive high quality grounded explanations to improve AI-patient communication.

Personalization

Human-centered decision-making requires personalized, resource-efficient, and equitable solutions. We consider a framework with a single statistical model for a given task where the human-centric data is incorporated into the state or influences the objective, actions, or constraints. Framed in the formalisms of sequential decision making, a belief state distills relevant information from a history of observations, to choose actions based on a policy that is optimal in maximizing reward for each specific subject. Such a policy is personalized by the context provided by information about the individual gathered from data integration or from human instruction. Instructability dictates that as additional human input is given, any policy is flexible such that a modified state based on the observed instructions ensures actions that satisfy these instructions. Once a state representation is informed with human feedback and personalized data, it provides the basis for optimizing policies. Human interpretation of uncertainty quantification in the state is essential. Users would benefit from knowing how trustworthy the machine prediction is, especially in health care.

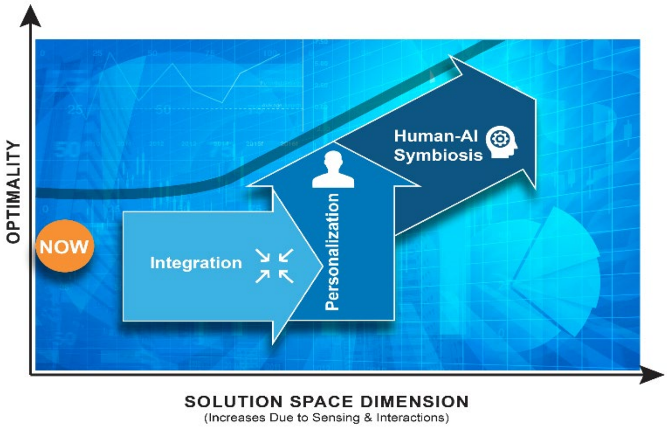
The importance of digital twins in personalization. Digital twins couple computational models with a physical counterpart[26–28] that can be dynamically updated through bidirectional data flow as conditions change.[29] Biophysically based models have the potential to improve biomedical decision-making at the individual level, but generating models capable of directly informing patient treatments remains a significant challenge,[30] as generic models are insufficient for characterizing population diversity,[31,32] necessitating personalization. Personalization requires measurements of the parameters underlying a model through batteries of sensor-based data collections, which can be exceedingly difficult and costly.[33] This motivates the improvement of the efficiency and precision of parameter determination to ensure alignment at the level of an individual. Ideally, one could decode (solve the inverse problem) of identifying the digital twin's parameters from an individual's state representation, itself computed from integrative multimodal processing including self-supervised learning, which will greatly improve the quality of personalization by capturing the relevant information about a given individual. Then, the digital twin can enable subsequent simulation from the individual's state. The digital twin-based simulations themselves will create virtual data that can be fed back to the integrative multimodal data processing and used to compare to the original state presentation and decoded parameters, with cyclic loss functions that penalize the differences used to update decoder and in updates of the integrative multimodal processing. Finally, models capable of capturing the long-term dynamics of the state can be used with the digital twin to simulate future states.

The current state-of-the-art for digital twins include NVIDIA's OmniVerse, which bridges collected data and AI systems with the 3D world building. This can link video/motion capture and sensor measurements with the digital twin. OnmiVerse (and by extension, IsaacSim and IsaacGym) provides a common platform that has the capabilities to intake data and models and seamlessly and efficiently *integrate reinforcement learning and other AI algorithms with physics engines*. IsaacSim provides a robust physics engine for model patients in rehabilitation and IsaacGym provides tools for seamless integration with reinforcement learning, enabling optimization of control algorithms for various robotics platforms, as in our previous work.[34] To be realistic it will require mechanistic models or data from these mechanistic models (e.g., OpenSIM,[35] MuJoCo[36]) that are regularly used to model biomechanics and rehabilitation processes. These widely tested and validated models can be used to create the initial digital twins.

Human-AI Symbiosis

Alignment of AI decision making can use hybrid RL that merges offline data (collected from human behavior) with online simulations involving digital twins to provide a means to produce optimal policies that are supported by human behavior. When users exploit AI-aided decision making, their new behavior is a step toward optimization, and their new behavior can be used in subsequent AI policy optimization. Through iterations, this will enable human-in-the-loop co-evolution of policies that can safely explore increasingly complicated decision spaces—achieving unprecedented optimality as shown in Figure 3. We envision human-AI co-evolution to explore the policy space efficiently and safely, while maximizing measurable and functional outcomes.

Figure 3. Evolution of AI in Rehabilitation



Establishing a trustworthy human-AI team is crucial for human-centric decision-making and actions, especially in rehabilitation with clinical intervention and robotic assistance. There is a need for cross-cutting approaches to measure human trust at behavioral and neural levels, where trust in human-autonomy interaction is defined in situations characterized by uncertainty,[37] based on extracting levels of human trust in AI-driven agents through real-time monitoring of neural correlates.[38] In particular, EEG may be used to quantify in real-time the effectiveness of human-AI teaming.[38] This real-time estimation of trust is a pivotal factor in guiding the AI system to align with the human teammate, revolutionizing the effectiveness of human-AI cooperation. This can be extended to cases where trust has to be repaired.[39] When trust is established, we expect Human-AI symbiosis to emerge as the AI becomes better adapted to meet the needs and as communication modes of human collaborators and the human collaborators better understand how to communicate and benefit from AI capabilities.

While improved sensing can provide functional and structural information, and patient questionnaires can provide understanding of activities and participation, the ability to understand how a patient feels or discomfort is poorly quantified. We envision using natural language-based interactive patient dialogues with patients that build trust and a better understanding of patient perspectives. Long term, we envision deriving neural correlates of reward to directly guide the AI adaptation, which was proposed by our team for brain-machine interfaces[40] and has been improved steadily in animal models.[41] Brain machine interfaces provide a motivating use case of human-AI symbiosis in rehabilitation, where the machine directly senses and decodes the brain's activity regarding musculoskeletal control and reward to control external robotics (exoskeletons).[42] A key lesson from our research[40] is that the brain of each subject is not only unique but changes day to day,[43] one of the challenges and potentials of aiding in neuromuscular rehabilitation. Building on our work in stroke rehabilitation,[44] there is the potential to combine EEG-based correlates of reward with muscle activity in closed-loop robotics and a virtual avatar to induce neuromuscular synchrony to speed recovery.

Predictive modeling for AI-powered robot-assisted personalized interventions. Our prior research demonstrated that complex neuromusculoskeletal models could simulate robot-assisted therapies for both healthy individuals[45,46] and those with mobility impairments.[47] These models effectively replicate healthy and impaired walking with high accuracy, yet they fall short in capturing motor learning and adaptation—key elements in the rehabilitation process. AI may be able to predict how patients adapt to specific robot-assisted interventions, by modeling the process of motor learning at the brain level. This breakthrough has the potential to revolutionize sensorimotor rehabilitation by introducing a new generation of modeling frameworks. This approach allows therapy interventions to be simulated, optimized, and personalized before being applied during treatment, allowing for a more targeted and effective therapy experience. The ability to model and thus simulate rehabilitation will be essential for further enabling personalized decision making and digital twinning. A range of wearable technology and robot-assisted rehabilitation devices can be integrated into the simulation environment. Doing so allows us to fine-tune various parameters—such as intervention type, frequency, and therapy duration—to achieve better functional outcomes. The ultimate goal is to create interventions that effectively promote motor adaptation, improving each individual's rehabilitation.

Accessible Natural Language (NL) Interfaces. Human-AI partnering means that there must be interaction between the machine and the human that is understandable and grounded for both the AI and the human. The AI interfaces must themselves be adaptable and tailored to interact with clinicians (for AI partnering) and end-users (patients). A participatory user-centered design practices should be adopted involve practitioners, their clients, and other stakeholders throughout the design process, starting from involving diverse stakeholders in the requirements gathering and using ethnographic observations, contextual inquiry, group and individual interviews, and having them interact with a series of iterative prototypes leading to validation in randomized control trials. Interacting with the patients requires extra care in safety.[48] In addition, patients in our studies may experience aphasia or other cognitive impairments which must be accounted for in the participatory design process—previous projects began to tackle these challenges.[49–52] Research on health and rehabilitation has a particular onus to reach vulnerable and underserved populations due to significant health disparities and disparities in social determinants,[53] such as education, employment, and socio-economic status. People with disabilities are one such vulnerable group.[54] To ensure accessibility, communications generated by AI systems should be personalized through multiple communication modalities to achieve the concept of "born accessible".[55] Accessibility comes in many forms including being able to translate between graphics and text taking into account characteristics of the reader,[56] and text simplification. It could also mean adapting suggestions to users who may need different support or may respond to different therapeutic exercises with varying degrees of enthusiasm[57] or who might engage more or less with certain types of interfaces—including the choice of AI personalities.[58]

AI ethics framework. There is a threat of both under- and over-estimation of the risks of AI, so the study of AI ethics must weigh risks and prioritize mitigation strategies. An ethics framework for rehabilitation and physical therapy integrates standard-of-care guardrails for treatment, e.g., patient consent-to-treat and maintenance of patient-therapist trust. The ethics framework will need to respond to functional gains of AI by supplying programmed constraints[59] in human-AI cooperation applications, such as in AI-enabled personalized healthcare interventions.[39]

Conclusion

With human-AI symbiosis, new possibilities for optimizing rehabilitation interventions are supported as the continual adaptation of empirical and biophysical models and expert behavior over time gather supporting evidence at the cutting edge. Together, this will support human-AI co-evolution of new policies—accelerating the exploration of possibilities while still guided by human expertise. Creating AI systems that enable these transformative capabilities will require many components and diverse expertise as outlined in this work.

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