Human-machine interfaces (HMI) record biosignals generated by humans – such as neural (brain), visual (gaze), or limb movement – and decode them into control inputs for assistive devices such as prosthetic limbs. However, their clinical adoption remains limited because most conventional interfaces cannot adapt to diverse users, resulting in low usability and high abandonment rates among people with motor impairments [1]. There is a need to seamlessly tailor biosignal-based HMI to diverse users and tasks, providing an "out-of-the-box" solution that requires no expert setup [2]. This problem has traditionally been challenging due to the high variability of biosignals [3] – humans interact with interfaces differently and adapt over time – requiring extensive interface calibration. My research addresses this challenge by **modeling complex human behaviors in HMI and personalizing interfaces based on individual needs and abilities**. I leveraged theoretical frameworks in control theory, neuroengineering, and data-driven methods to **(1) model humans** as control systems interacting with machines [4] to investigate user strategies and adaptations in multimodal HMI, and use these insights to **(2) design interfaces that co-adapt in real time** – that is, adapt in response to user's ongoing adaptation [5]. Understanding human control strategies not only informs the underlying dynamics of behaviors, but also provides interpretable objective functions to apply in optimization tools. For instance, in robot-assisted rehabilitation, modeling patient behaviors interacting with the robot will help caregivers predict recovery and provide optimized robotic intervention.

During my PhD, I integrated systems with multimodal inputs, including surface electromyography (EMG), eye tracking, gestures, and manual joystick. I designed studies with healthy participants controlling a virtual machine (cursor with dynamics), and used experimental data to model user strategies, preferences, and adaptation. We learned that humans coordinated multiple inputs differently based on individual motor abilities and preferences for enhanced accuracy and stability [6,7]. This highlights the importance of tailoring HMI to each individual. I then applied the model to design an interface that continuously adapts the machine dynamics to optimize for its objective of assisting the user [8]. We investigated the dynamic interactions between humans and adaptive machines, and showed that co-adaptation significantly improved performance and reduced user effort. We further found that people co-adapted with the machine differently, resulting in distinct convergence patterns across users. Moreover, I leveraged the abundant information from multimodal signals to build a new framework for interface adaptation in diverse tasks. I demonstrated it by modeling user intent with gaze in an EMG-controlled interface [9], allowing continuous calibration even when the task goal is not apparent, such as writing or drawing with a computer cursor. In summary, **my research on modeling strategy and co-adaptation provides new theoretical and experimental frameworks for personalizing multimodal HMI to diverse users and tasks.** Moving forward, I plan to implement the frameworks in rehabilitation programs, such as robot-guided therapy, to deliver personalized interventions [10] for people with motor impairments. Together, this will enhance the usability, generalizability, and clinical translation of biosignal HMI.

<u>REFERENCES:</u>

1. Farina, Dario, et al. "The extraction of neural information from the surface EMG for the control of upper-limb prostheses: emerging avenues and challenges." IEEE Transactions on Neural Systems and Rehabilitation Engineering 22.4 (2014): 797-809.
2. **<u>Chou A. H.Y.</u>**, Madduri M., Li S.J., Burckhardt S., Christensen A., Hutchison F., Orsborn A. L., Burden S. A. “Design principles for co-adaptive, multimodal interfaces”. ACM SIGCHI ’24: Human-Factors in Computer Systems, PhysioCHI Workshop: Towards Best Practices for Integrating Physiological Signals in HCI. May 2024.
3. Artemiadis, Panagiotis. "EMG-based robot control interfaces: past, present and future." Advances in Robotics & Automation 1.2 (2012): 1-3.
4. Yamagami, Momona, et al. "Effect of handedness on learned controllers and sensorimotor noise during trajectory-tracking." IEEE Transactions on Cybernetics 53.4 (2021): 2039-2050.
5. Madduri, Maneeshika M., Samuel A. Burden, and Amy L. Orsborn. "Biosignal-based co-adaptive user-machine interfaces for motor control." Current Opinion in Biomedical Engineering 27 (2023): 100462.
6. **<u>Chou, A. H.,</u>** Yamagami, M., & Burden, S. A. “Evaluating a human/machine interface with redundant motor modalities for trajectory-tracking,” IFAC-PapersOnLine, vol. 55, no. 41, pp. 125–130, Jan. 2022.
7. Hutchison L., **<u>Chou A. H.Y.,</u>** Burden S. A. “Modeling Human Control in Multimodal Human-Machine Interaction”. IEEE Engineering in Medicine and Biology Society (EMBC). July 2025.
8. Yamagami, M., Madduri, M. M., Chasnov, B. J., **<u>Chou, A. H.,</u>** Peterson, L. N., & Burden, S. A. . “Co-adaptation improves performance in a dynamic human-machine interface”. bioRxiv, July 2023.
9. **<u>Chou, A. H.,</u>** Madduri, M., Li, S. J., Isa, J., Christensen, A., Hutchison, F. L., ... & Orsborn, A. L. “Using Eye Gaze to Train an Adaptive Myoelectric Interface. bioRxiv, April 2024.
10. Cashaback, J. G., Allen, J. L., **<u>Chou, A. H..,</u>** Lin, D. J., Price, M. A., Secerovic, N. K., ... & Miller, H. L. "NSF DARE—transforming modeling in neurorehabilitation: a patient-in-the-loop framework." Journal of NeuroEngineering and Rehabilitation 21.1 (2024): 23.