Agentic Wearables: Sensor-Informed Intelligent Systems for Autonomous Health Support

I envision a future where intelligent systems provide us with just-in-time, personalized health support during everyday life. Advances in wearables, smartphones, and other mobile health (mHealth) technologies provide an unprecedented opportunity to complement clinical care and fill a critical gap in health care delivery. Sudden bouts of symptoms (e.g., panic attack) and the need for continual behavior change are hallmarks of mental and chronic illnesses, requiring timelier support than can be clinically initiated.[1] Yet, much of the latest work on AI for wearables focuses on interpreting sensor data for routine clinical support,[2] leaving the gap in autonomous everyday support unaddressed.

My research addresses this gap by enabling intelligent systems that *autonomously* provide health support, leveraging *sensor data* and *online learning* for personalization. A difficult yet remarkable aspect of health care delivery is that the same exact intervention can produce vastly different outcomes when delivered in different contexts or to different people. My research addresses this need for precision and personalization by **focusing on three components of AI systems for autonomous mHealth support (Figure 1)**. Sensor data can be used to infer an individual's biobehavioral context or "state." Digital twin models can accordingly predict the effects of intervention decisions on outcomes. Decision-making algorithms can then optimally control interventions to improve outcomes. For each component, online learning enables individualized training on incoming data to optimize future inference and decision making.

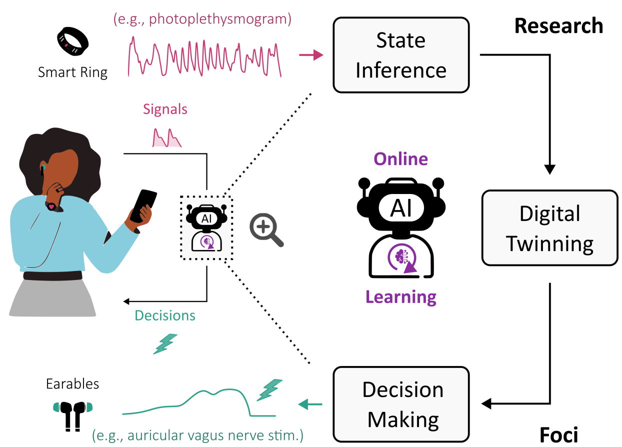

Figure 1: Research program on "agentic wearables." My program's three foci enable the next generation of sensor-informed closed-loop systems for mHealth support.

Three interlaced **c**hallenges motivate my past contributions and lab's future research directions:

C1) Modeling and inference errors can cause personalized support to backfire. If a system suggests a person de-stress when they are in fact relaxed, confidence in the system can reduce and lead to disengagement. Wearable sensor data is often corrupted, and predictions of states like stress are fallible. Autonomous systems must account for these uncertainties to personalize support intelligently.

C2) Quantitative models to inform decision making are lacking. Mechanistic models in behavioral science are often qualitative, while data-driven models often ignore person-specific differences and struggle notoriously with group-to-individual generalizability. Models are needed that account for between-person heterogeneity and leverage domain knowledge to overcome blindspots in data.

C3) Current control systems focus either on behavioral or biological interventions, each with distinct modes of operation. Behavioral interventions (e.g., mindfulness reminders) require conscious engagement, which is impractical if suggested too often or in moments like panic. Biological interventions (e.g., neuromodulation) bypass consciousness but are riskier and do not promote self-efficacy.

To address C1, C2, and C3, my lab will build upon the foundation laid by my prior work and pursue three specific research **d**irections: **D1) uncertainty-informed, online decision making** for precision health support, **D2) hybrid modeling for digital twin design** informed by domain science, and **D3) optimal control of biobehavioral intervention systems** to enable the next generation of autonomous systems for personalized health support – accessible in everyday life.

[1] M Ghahramanlou-Holloway, *Psychiatry*, 2022 [2] D A Adler et al., *ACM IMWUT*, 2024