Health Systems Engineering & Informatics Laboratory

Research Mission

The **Health Systems Engineering & Informatics Laboratory** aims to advance the science of health systems through interdisciplinary research that integrates theories and methods from informatics and cognitive engineering. Our mission is to study, develop, and translate innovations that enhance clinical decision-making, improve patient and public health outcomes, and promote health equity.

Model-agnostic Interpretability for Clinical Machine Learning

As health systems increasingly adopt black-box machine learning models for clinical and operational purposes, the need for interpretability has become critical. While these models are promising it terms of performance, their complexity often makes it difficult for end-users to understand how decisions or recommendations are made, limiting their trust and use in decision-making. Our research focuses on model-agnostic interpretability techniques specifically for temporal models. Traditional interpretability methods such as Shapley Additive Explanations (SHAP) can be computationally expensive and may not be well-suited for time-series data such as longitudinal electronic health record data and continuous monitoring data in acute care settings. We have developed, for example, a revived approach called *WindowSHAP* to address these challenges and advance the interpretability of clinical machine learning models, regardless of their underlying model architecture. Key research questions we are exploring in this area include: How do inherently interpretable models compare against model-agnostic interpretability methods in the context of time-series clinical data? What theories and methodological approaches challenge the notion of performance-explainability trade-off in real-world clinical applications? What are the most effective post-hoc explainability methods for various end-users, including clinicians and engineers? In what ways do those methods foster clinician trust and patient safety?

Digital Phenotyping

Computable Clinical Phenotypes for Precision Medicine

Accurate and reliable phenotyping is essential for conducting robust observational studies and designing adaptive and safe clinical decision support systems. A significant part of our research involves developing algorithms and methods to effectively identify computable phenotypes for a range of conditions including traumatic brain injury, acute respiratory failure, and post-acute sequelae of SARS-Cov-2 (PASC or Long COVID). We use both rule-based algorithms and representation learning methods to address complexities of using routinely collected clinical data for research purposes. The following are our prime examples and outcomes of our work related to computable phenotypes.

* We have developed and validated first of its kind rule-based electronic phenotyping algorithm to classify patient records based on type and sequence of respiratory support received, among other critical factors.
* Using a representation learning framework, which we designed, we have identified distinct phenotypes of traumatic brain injury that can potentially inform future clinical trials as well as personalized interventions.
* We have also demonstrated computable phenotypes for defining and characterizing long-term effects of SARS-Cov-2 infection (i.e., PASC) based on symptom duration, infection severity, and the presence of specific symptom clusters.

Cognitive Engineering & Clinical Decision-Making

To support our translational work, we study how decisions are made in real-world clinical environments, where traditional decision theories often fall short in capturing the true sociotechnical dynamics. For example, decision-making related to ventilation strategies for critically ill patients is a nuanced and complex challenge in acute care settings, where care teams must balance patient needs, available resources, and documentation workflows. We focus on key questions that clinicians face when deciding on ventilation strategies: determining when to start with non-invasive or invasive ventilation, selecting appropriate forms of non-invasive respiratory, and deciding when non-invasive methods have failed, necessitating intubation. On one end, we employ cognitive engineering methods to capture both the operational complexities of acute care settings and the cognitive expertise of clinicians. On the other end, we apply computational approaches to identify when and who might fail non-invasive ventilation therapies early enough to allow clinicians to intervene and potentially improve patient outcomes. Our findings provide a holistic view of the decision-making process related to ventilation therapies, as well as insights for designing and implementing clinical decision support systems that enhance cognitive support for clinicians.

Parking Lot:

This ongoing work builds on decades of decision-making research, emphasizing the need for decision-support tools grounded in naturalistic decision-making, macrocognition, and real-world clinical workflows to improve patient outcomes in complex care environments.