Using AI to Understand the Secrets of the Body

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Affiliated Faculty, UCSF Neurosurgery

Affiliated Faculty, UC Berkeley Statistics

November 20, 2026

Computational PRECISION HEALTH

Berkeley | UCSF

My interdisciplinary scientific journey

JOHNS HOPKINS UNIVERSITY





Prof. Sridevi Sarma

HST Harvard–MIT Health Sciences & Technology





Prof. Emery Brown

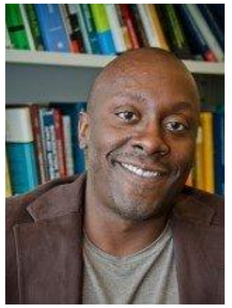


Prof. Riccardo Barbieri



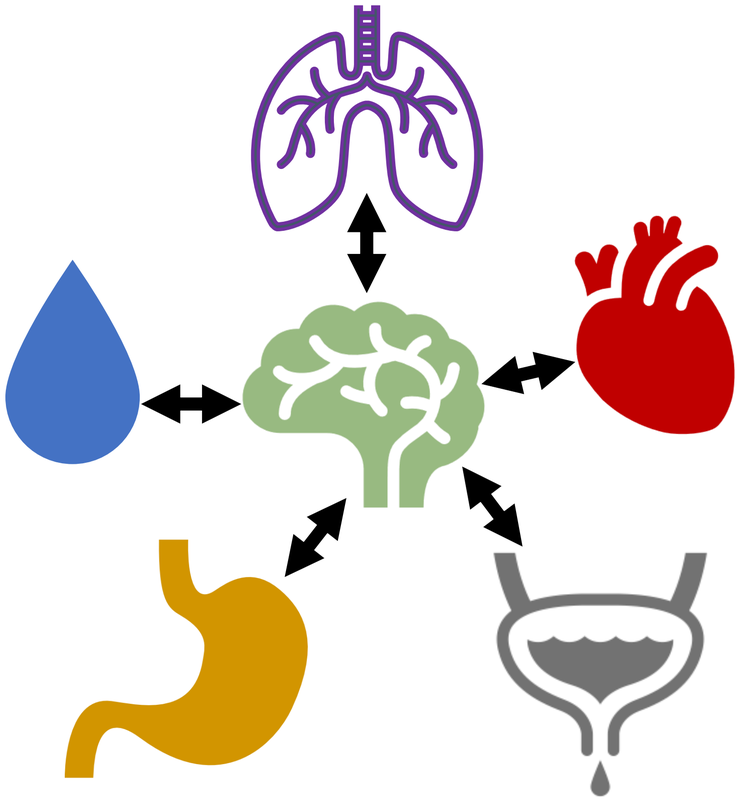


Prof. Sean Mackey



Prof. Todd Coleman

Why care about **brain-body** regulation?



There is unique and valuable information…

- ✓ When patients cannot communicate themselves
- ✓ Outside of the clinic
- ✓ That can add to what is communicated by patients
- ✓ In how regulation of basic functions changes with health
- ✓ In body-brain communication and feedback

Innovation is necessary at all stages of the pipeline!

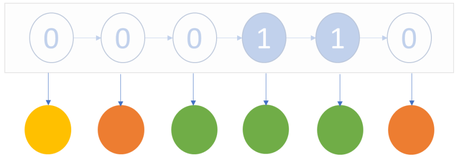
"Physiology-informed AI"

Data acquisition	Organ-level modeling	Multi-organ fusion

“Physiology-informed” AI

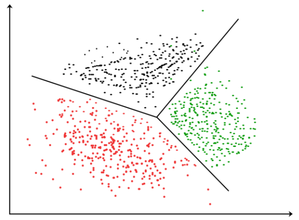
Point process methods

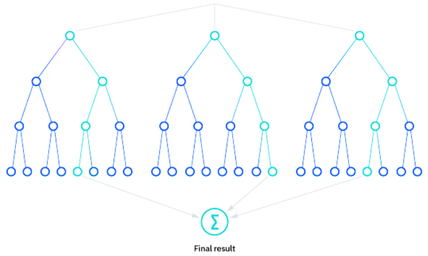


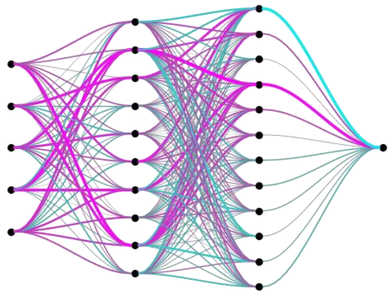


State space frameworks

Standard ML/AI tools

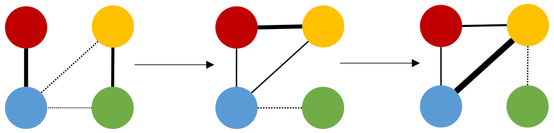






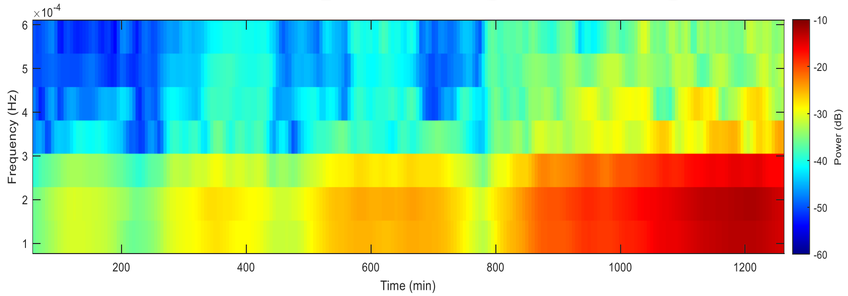
Differentiable modeling

Physiological principles, knowledge, and hypotheses



Network modeling

Time-frequency analyses



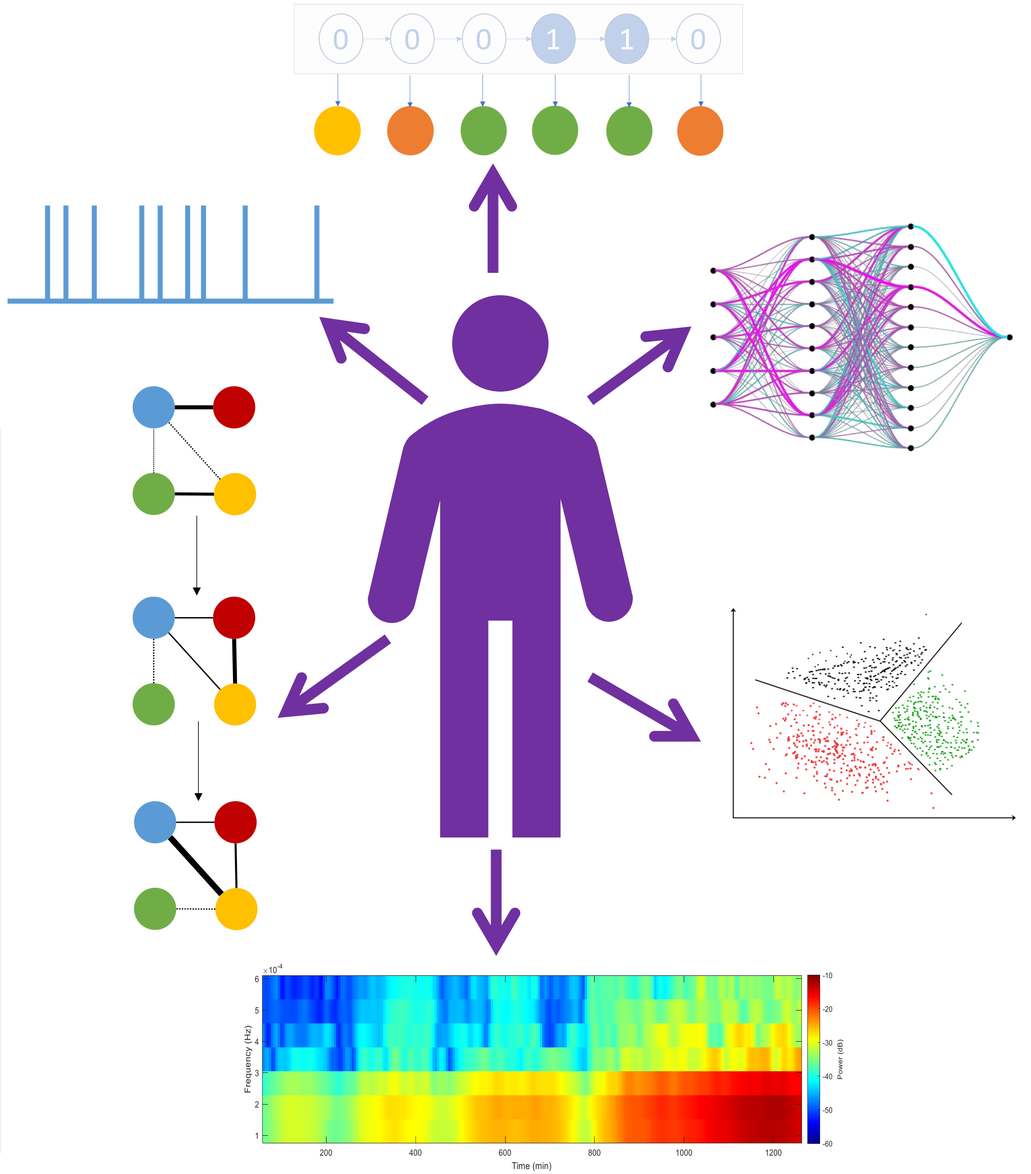
Subramanian et al. *IEEE EMBC* 2018
Subramanian et al. *IEEE EMBC* 2019
Subramanian et al. *ESGCO* 2020
Subramanian et al. *CinC* 2020
Subramanian et al. *IEEE EMBC* 2020
Subramanian et al. *PNAS* 2020
Subramanian et al. *PLOS One* 2021
Subramanian et al. *IEEE TBME* 2021
Subramanian et al. *PLOS Comp Bio* 2021
Subramanian et al. *Phys. Meas.* 2022
Subramanian et al. *IEEE EMBC* 2022
Subramanian et al. *IEEE TBME* 2023
Subramanian et al. *IEEE EMBC* 2023
Subramanian et al. ICLR Workshop 2024
Subramanian et al. *IEEE EMBC* 2024
Subramanian et al. *ICLR TS4H* 2024
Subramanian et al. *PNAS* 2024
Mohan et al. *IEEE EMBC* 2025
Dua et al. *IEEE EMBC* 2025
Chen et al. *IEEE EMBC* 2025
Mohan et al. *BayLearn* 2025
Mohan et al. *SfN* 2025

Key recurring physiological principles

1. The important information in physiological systems can be accessed through their generative processes

2. Physiological systems are connected and interdependent

3. Despite being nonlinear and complex, physiological systems often have hidden low-dimensionality

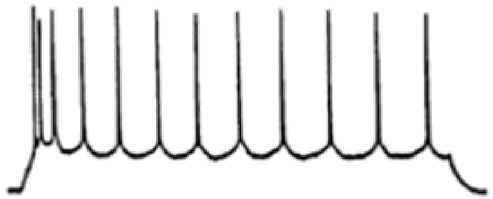


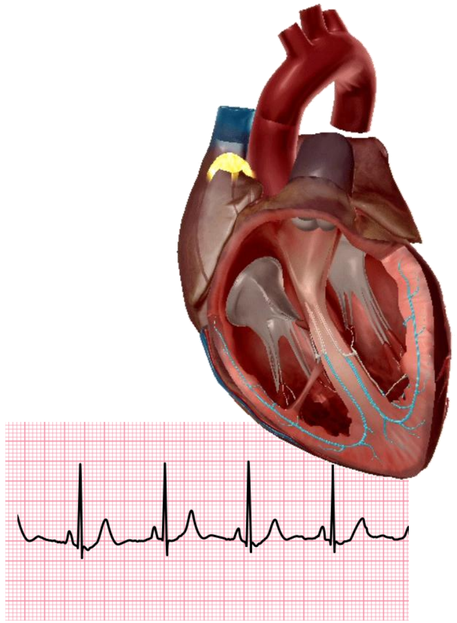
Point processes

Point Processes

Discrete binary events
in continuous time

Neuron Firing





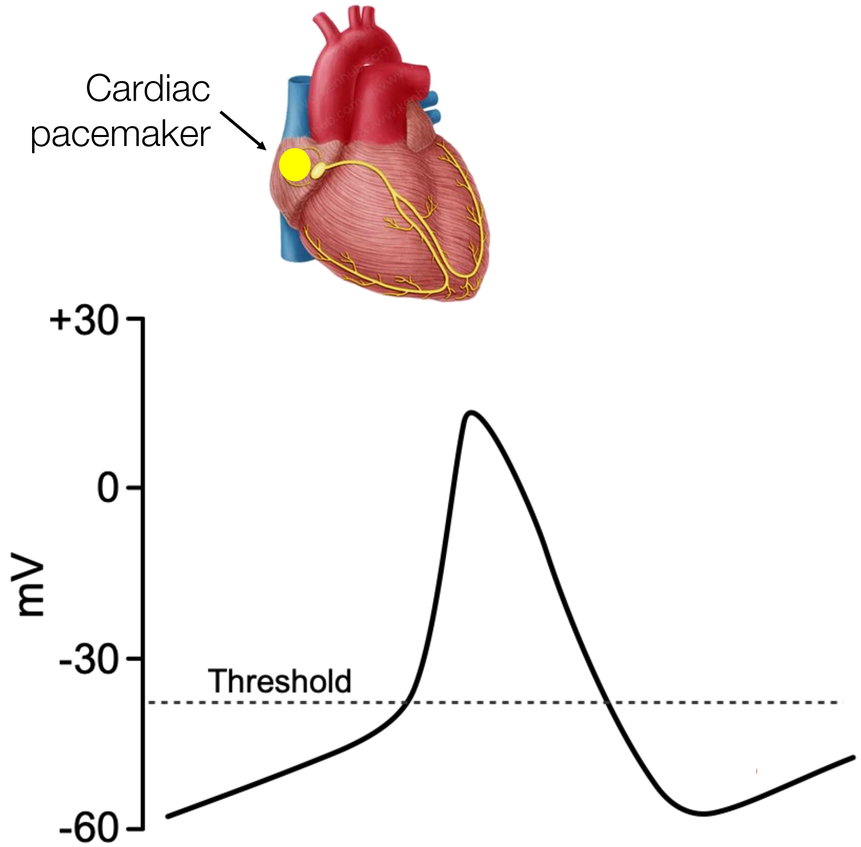
Cardiac Action Potential

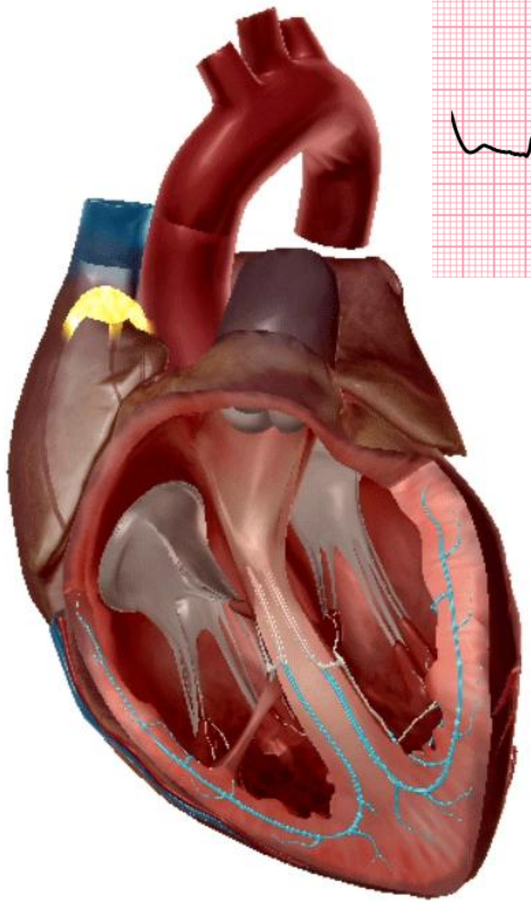
Conditional Intensity Function

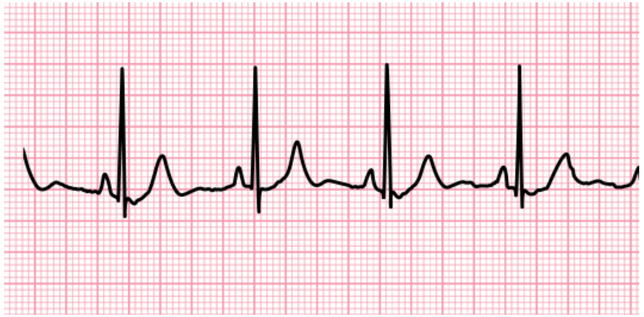
$$\lambda(t \mid H_t) = \frac{f(t \mid H_t)}{1 - \int_{u_{N(t)}}^{t} f(u \mid H_t)\, du},$$

Brown et al. *Neural Computation* 2002

The Cardiac Action Potential….







Animation from visiblebody.com

… is a point process!

Earthquakes



Geysers



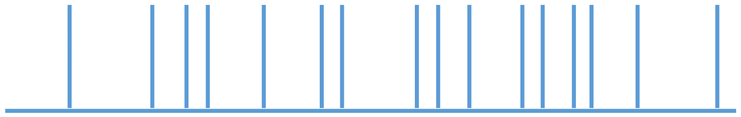
Volcanoes



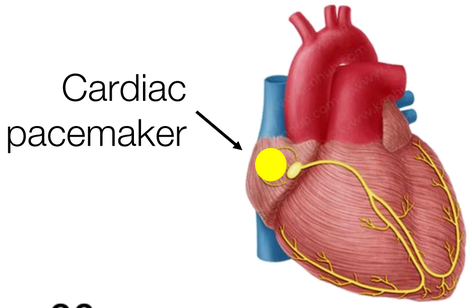


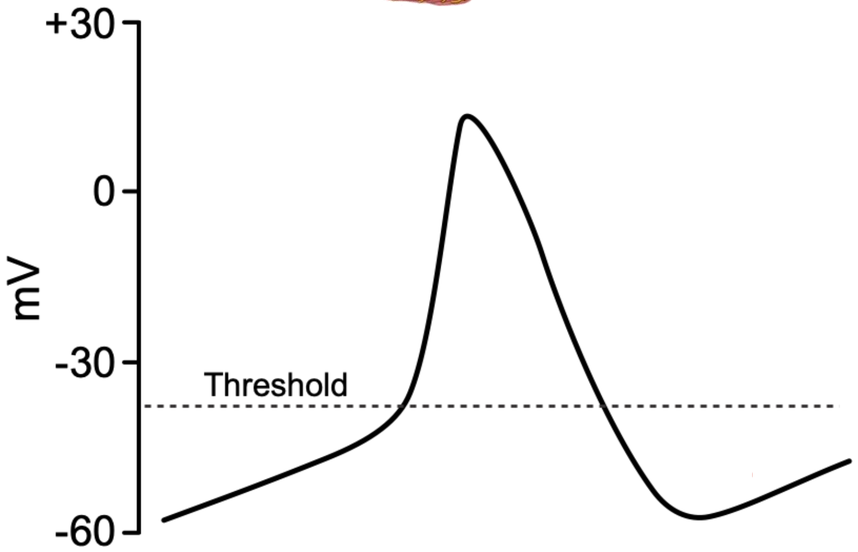
<u>Point Processes</u>

Discrete binary events in continuous time

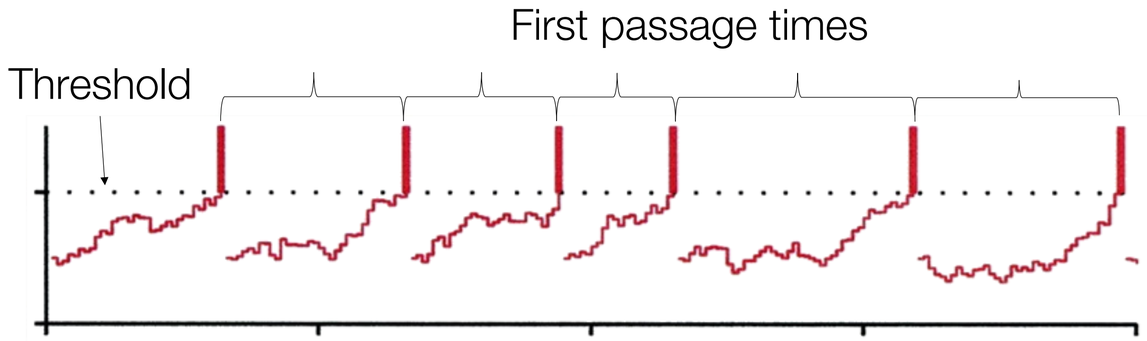


We can derive a model from the physiology



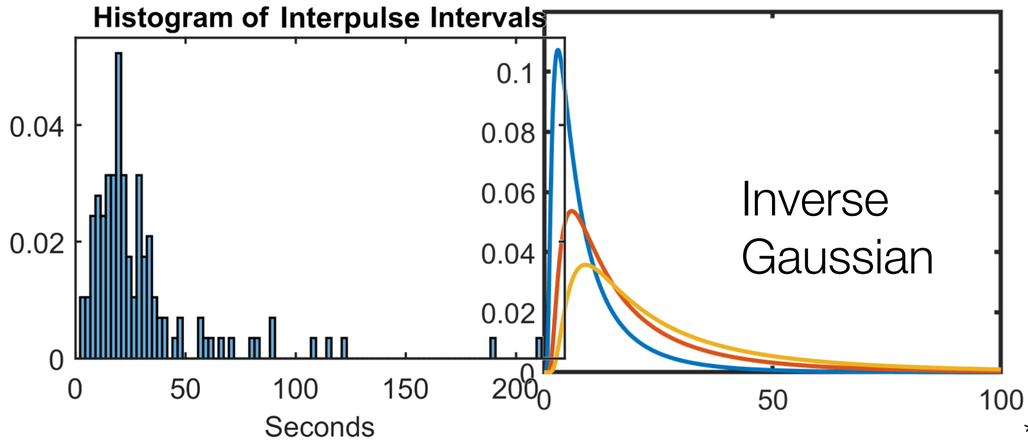


Gaussian random walk with drift



Adapted from Salinas & Sejnowski, 2000

Distribution of first-passage times is inverse Gaussian!*



*Schrodinger, 1915

Extracting physiologic information from heartbeat dynamics

INVERSE GAUSSIAN

$$f(x) = \left[\frac{\lambda}{2\pi x^3}\right]^{1/2} \exp\left\{\frac{-\lambda(x-\mu)^2}{2\mu^2 x}\right\} \qquad \begin{array}{l} x > 0 \\ \mu > 0 \\ \lambda > 0 \end{array}$$

HISTORY-DEPENDENT INVERSE GAUSSIAN

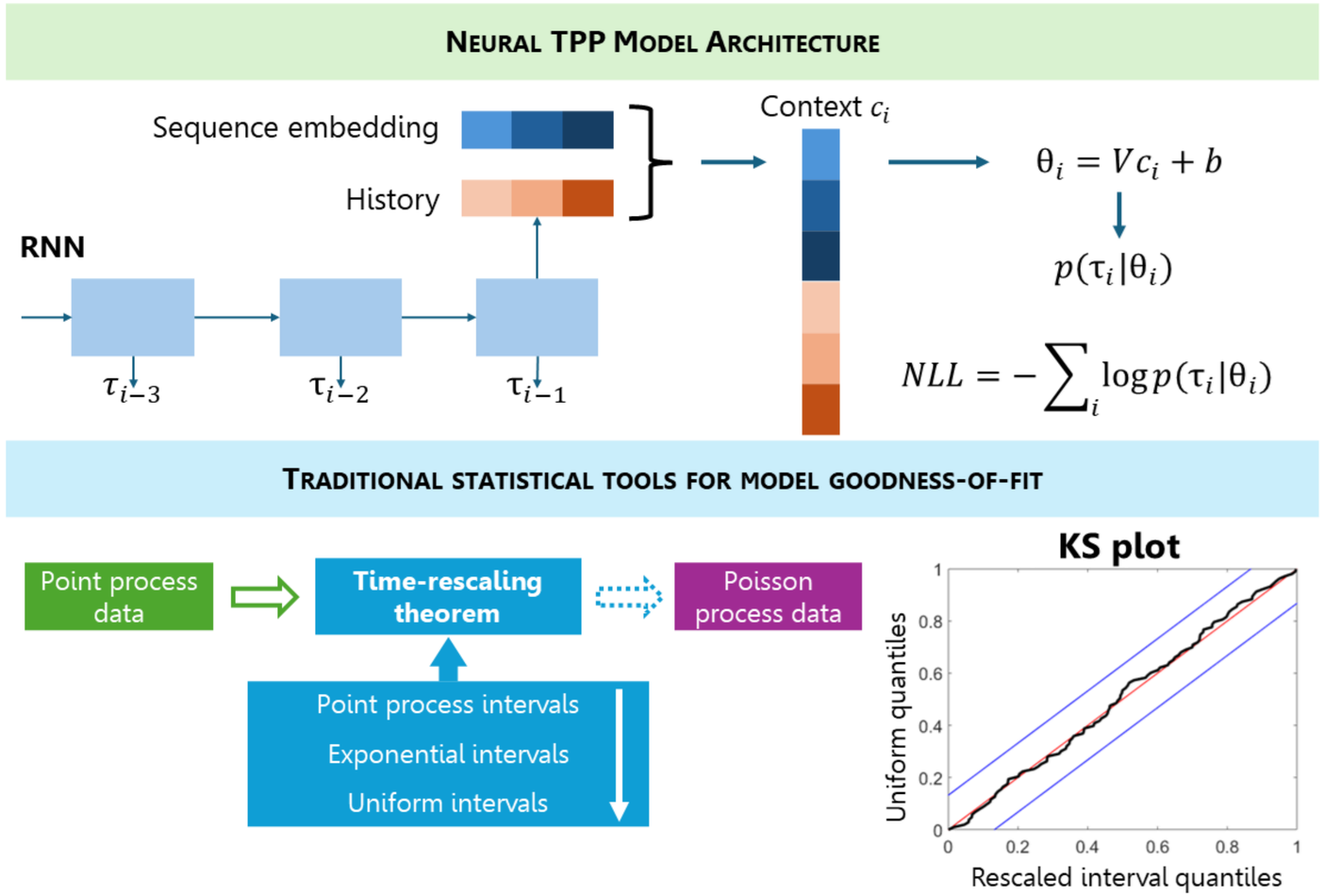
$$f\left(t \middle| H_{b_k}, \theta\right) = \left[\frac{\theta_{p+1}}{2\pi(t-b_k)^3}\right]^{\frac{1}{2}} * exp\left\{-\frac{\theta_{p+1}[t-b_k-\mu(H_{b_k},\theta)]^2}{2\mu(H_{b_k},\theta)^2(t-b_k)}\right\}$$

RR_k= kth inter-event interval $\qquad$ b_k= most recent event

$$\mu\left(H_{b_k}, \theta\right) = \theta_0 + \sum_{j=1}^{p} \theta_j RR_{k-j+1} > 0 \qquad \theta_t = (\theta_0, \theta_1, \ldots, \theta_{p+1})$$

Barbieri et al. 2005

Capturing long-range time structure in heart signals



Subramanian et al. *ICLR TS4H* 2024
Sunil et al. *BayLearn* 2026
Sunil et al. *bioRxiv* 2026

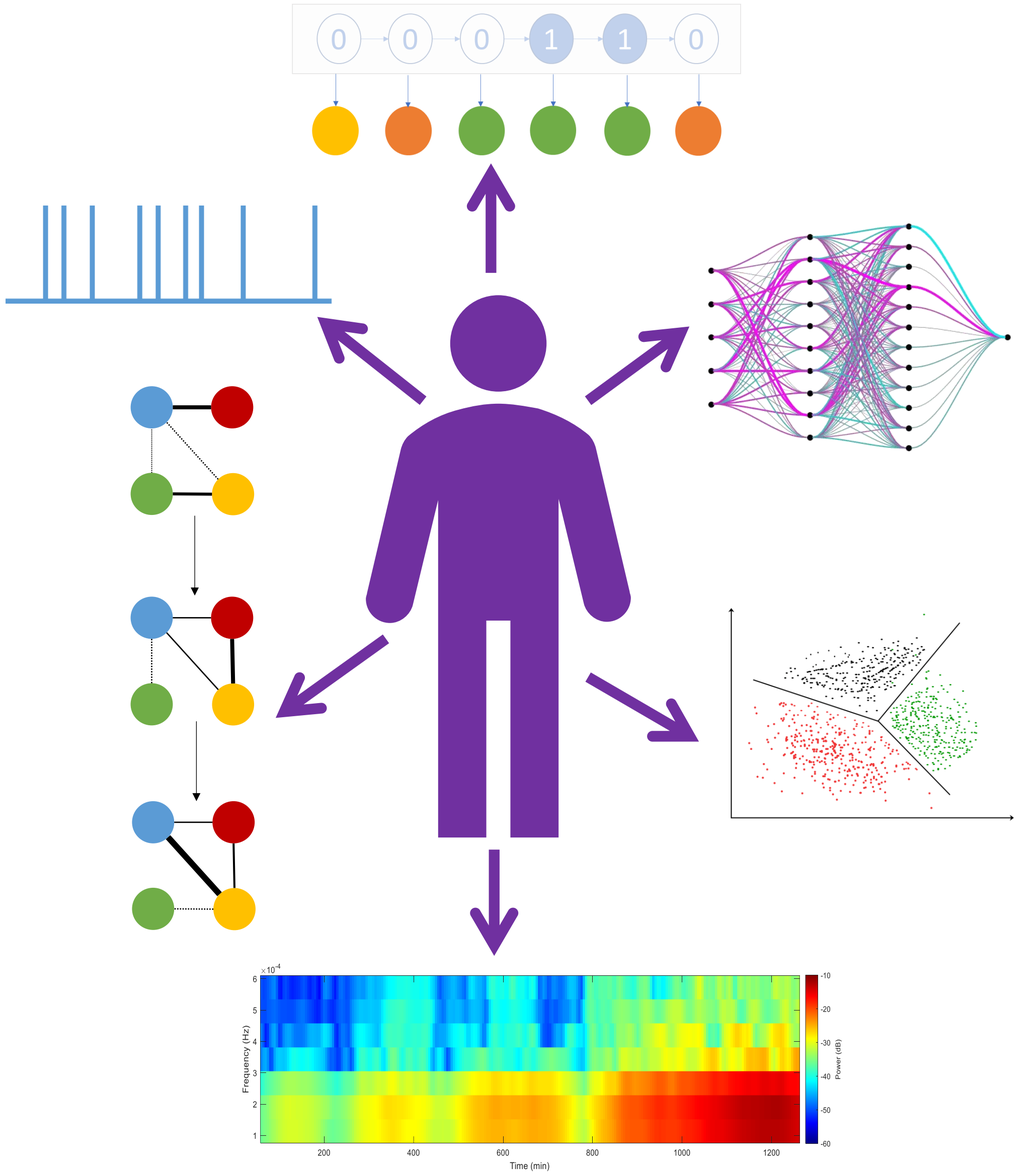


Key recurring physiological principles

1. The important information in physiological systems can be accessed through their generative processes

2. Physiological systems are connected and interdependent

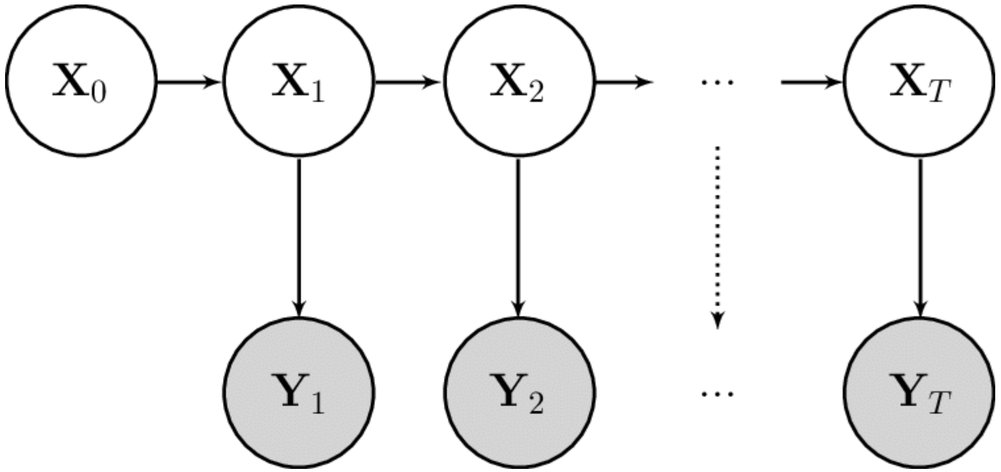
3. Despite being nonlinear and complex, physiological systems often have hidden low-dimensionality



Physiological systems are coupled in both time and space

Temporal connection

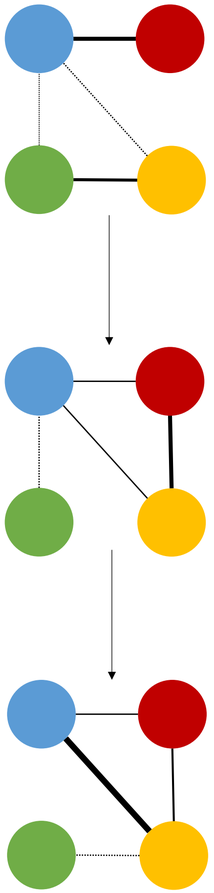
History dependence



- State space modeling
- Hidden Markov modeling
- Recurrent neural networks

Spatial connection

Coordinated communication



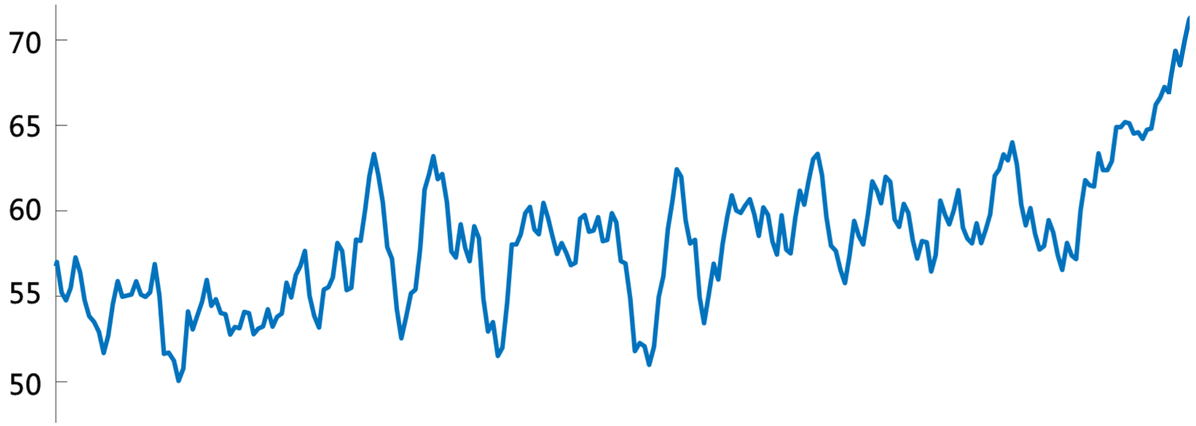
- Network modeling
- Graph theory
- Graph structure learning

State of the Art in 2025: Anesthetic management

Anesthesia = **Lack of pain processing** + unconsciousness + immobility + physiologic stability

Monitoring

HEART RATE



BLOOD PRESSURE

112/55 → 117/60 → 124/63 → 128/68

Management

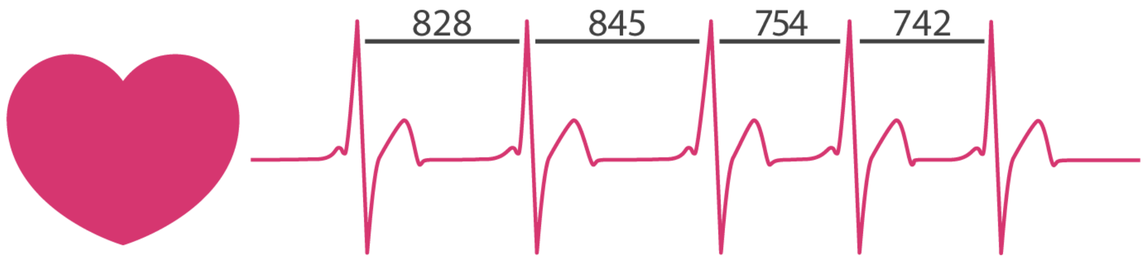
Is this a pain response?
"Big enough" pain response?

Give more medication?
Hold off and wait?

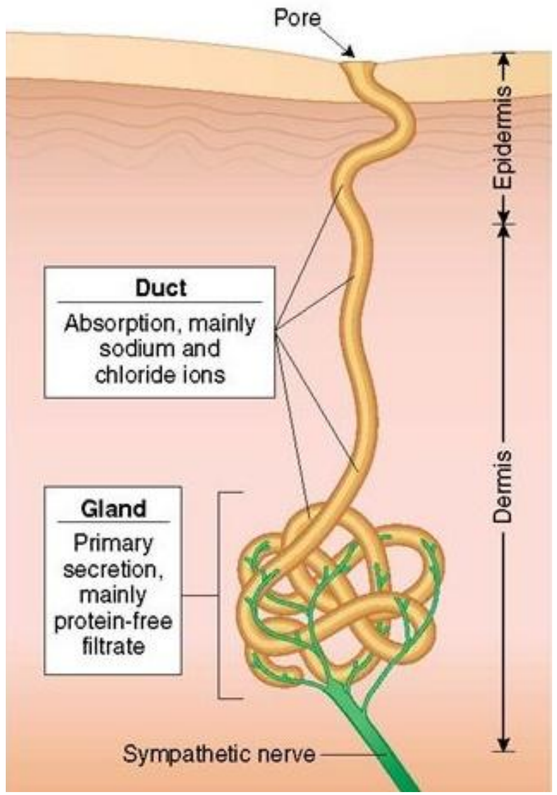
How do we quantify unconscious pain processing to guide anesthetic dosing during surgery?

Sourcing information from different parts of the fight-or-flight reflex

Heartbeat Dynamics



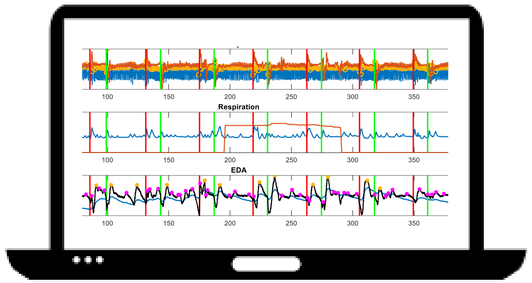
Electrodermal Activity



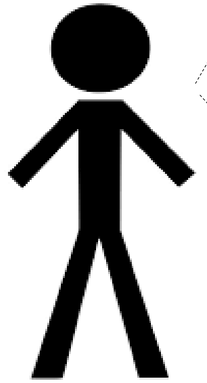
Our study design was optimized to study surgical pain



ECG + EDA signals



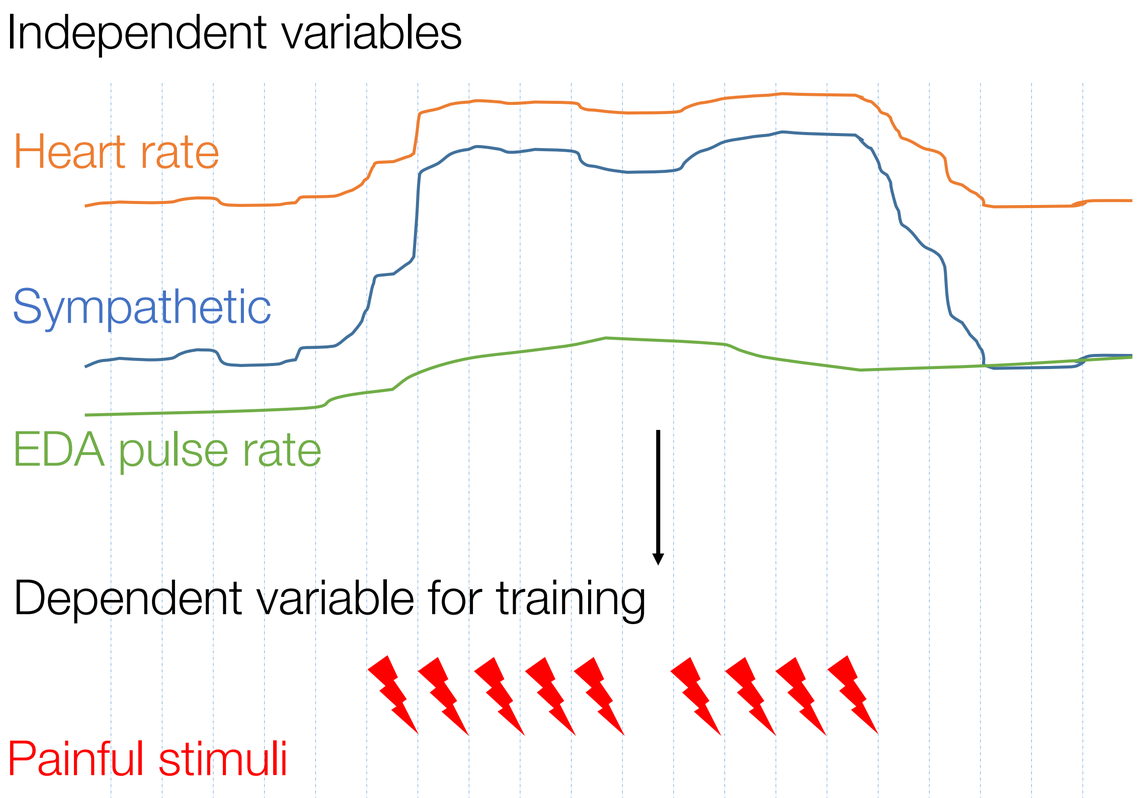
Annotate painful stimuli



Get times and doses of drugs given

Researcher

Interpretable model frameworks for unconscious pain



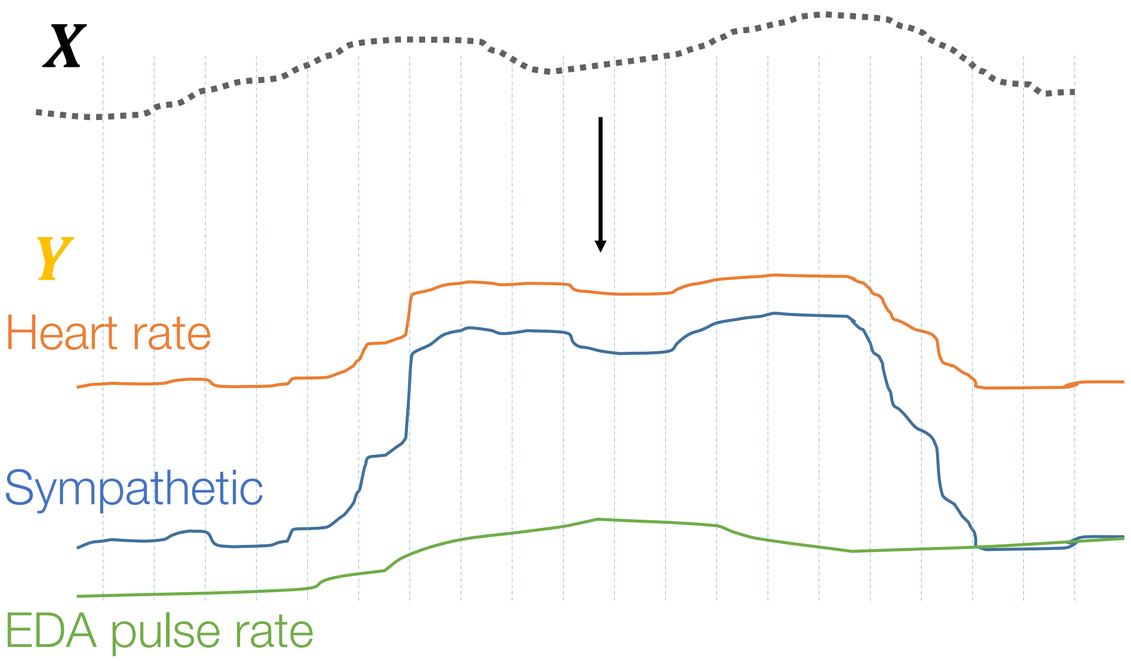
Supervised Frameworks

Logistic Regression

Random Forest

Subramanian et al. *PNAS* 2024

Interpretable model frameworks for unconscious pain



UNSUPERVISED FRAMEWORK

Linear Gaussian State Space Model

State model:

$$\boldsymbol{X_k} = F\boldsymbol{X_{k-1}} + v_k$$

$$v_k \in N(\mathbf{0}, Q)$$

Observation model:

$$\boldsymbol{Y_k} = A + B\boldsymbol{X_k} + \varepsilon_k$$

$$\varepsilon_k \in N(\mathbf{0}, R)$$

Subramanian et al. *PNAS* 2024

Example model prediction of unconscious pain state

PNAS ARTICLES FRONT MATTER AUTHORS TOPICS +

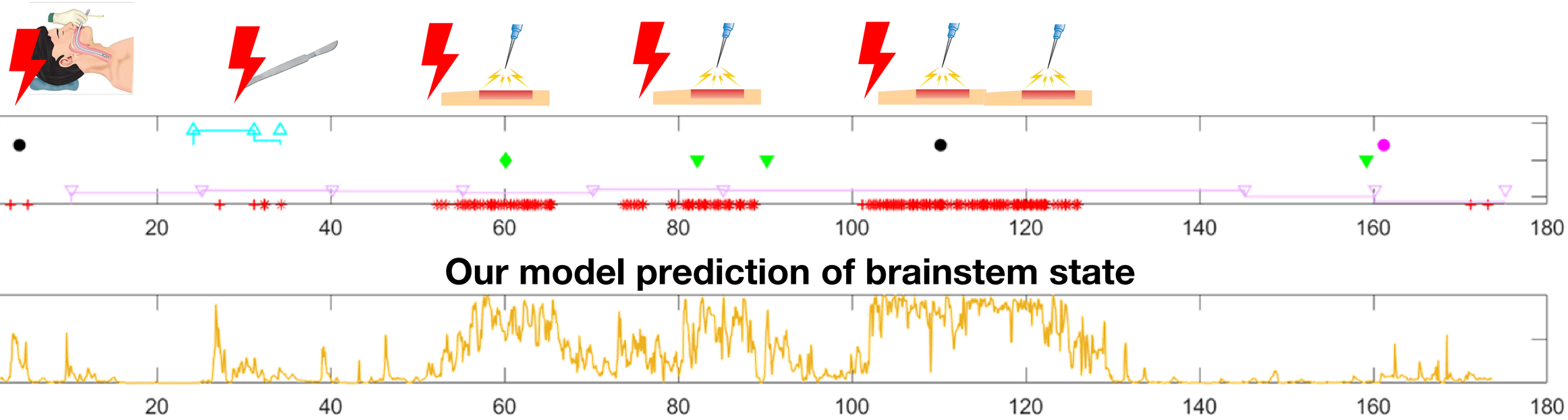
RESEARCH ARTICLE | NEUROSCIENCE |

Monitoring surgical nociception using multisensor physiological models

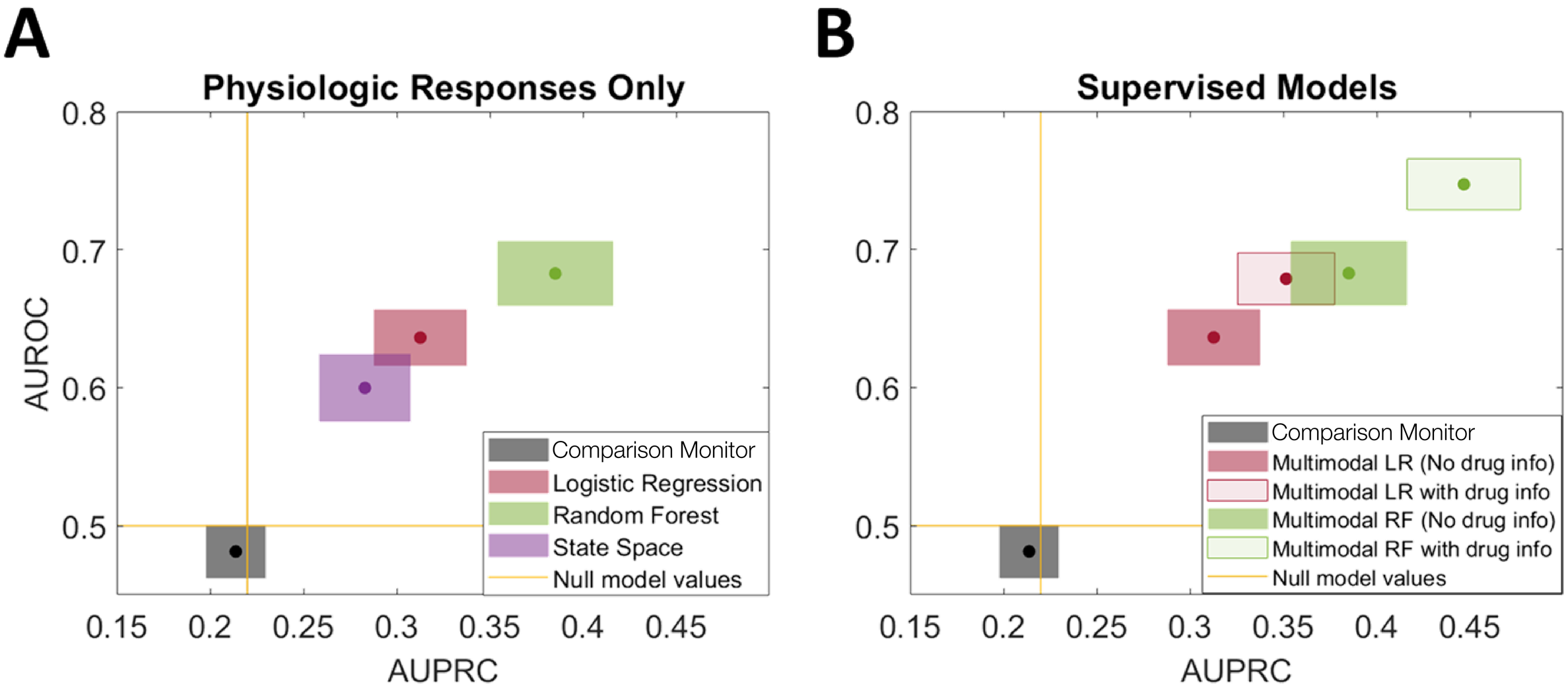
Sandya Subramanian, Bryan Tseng, Marcela del Carmen, +3, and Emery N. Brown Authors Info & Affiliations

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September 24, 2024 | 121 (40) e2319316121 | https://doi.org/10.1073/pnas.2319316121

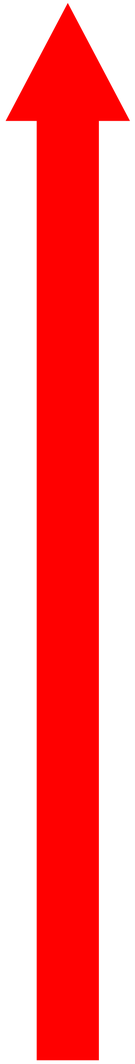


Model performances across 101 surgeries



Subramanian et al. *PNAS* 2024

The learned pain signature is physiologically consistent



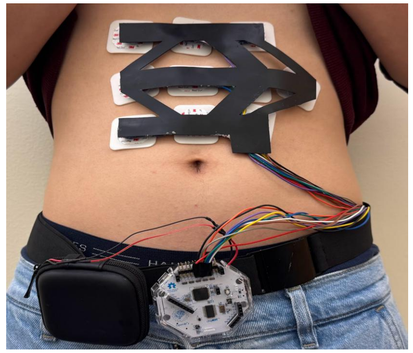
Learned pain signature

HEARTBEAT DYNAMICS
- Heart rate
- Sympathetic activity

SWEAT GLAND ACTIVITY
- Pulse rate
- Pulse amplitude

Subramanian et al. *PNAS* 2024

Leveraging coupled oscillators in the body

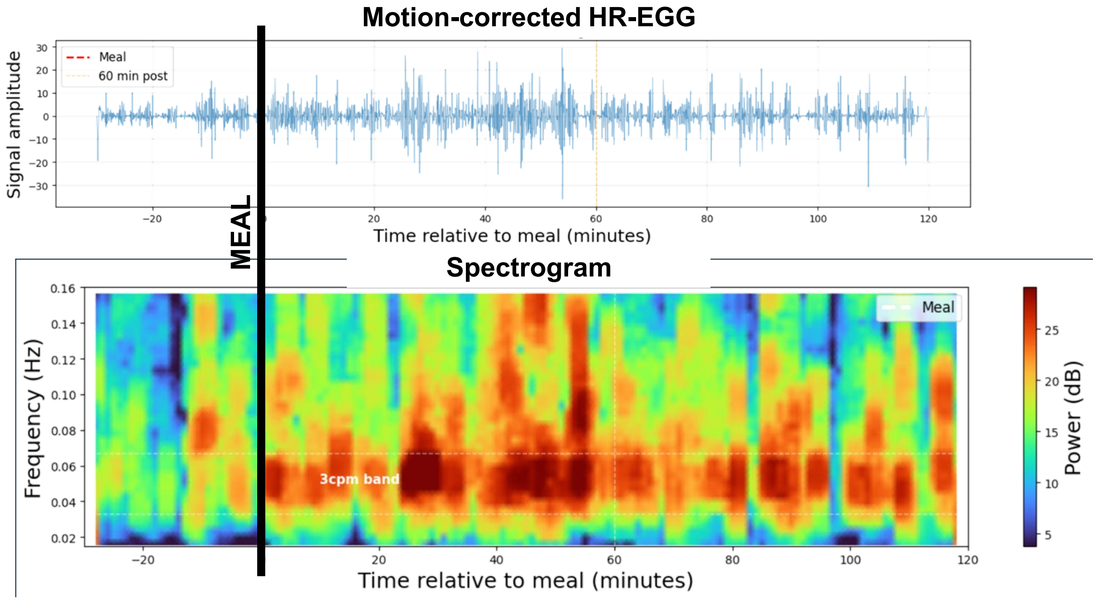


Wang et al. *Proc. IEEE EMBC* 2024

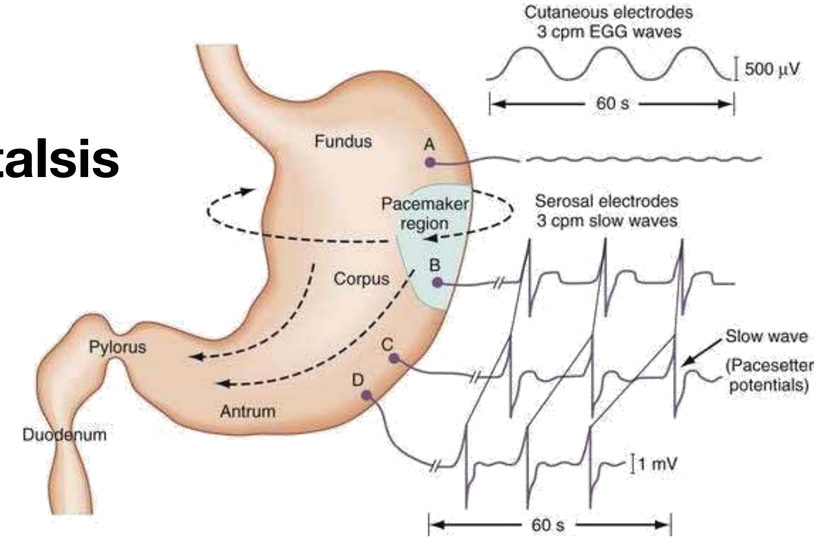
Improved spatiotemporal signal recovery from HR-EGG

$$\frac{\partial^2 u}{\partial t^2} - \|v\|^2 \left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right) = 0$$

$$\mathrm{PGD}(t) \triangleq \|\overline{v}\| \,/\, \overline{\|v\|}$$



Peristalsis



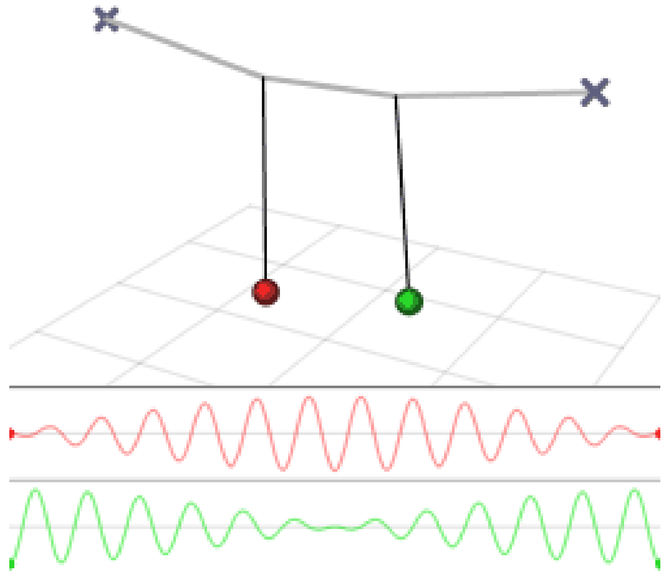
Coupled Oscillators

Coordinated oscillations in space and time

Modified from Coleman et al.
Modified from Koch *Electrogastrography* 2002

What is coupling?

Coupling – the parameters of one system or object affecting the parameters of another



Common with oscillators because they can transmit energy/vibrations between each other

- Pendulum
- Neurons
- Walking bridge
- **Stomach muscle?**

Many possible types of coupling: phase-phase, phase-amplitude, amplitude-amplitude

How do we model the stomach this way?

Data-driven approaches to coupling

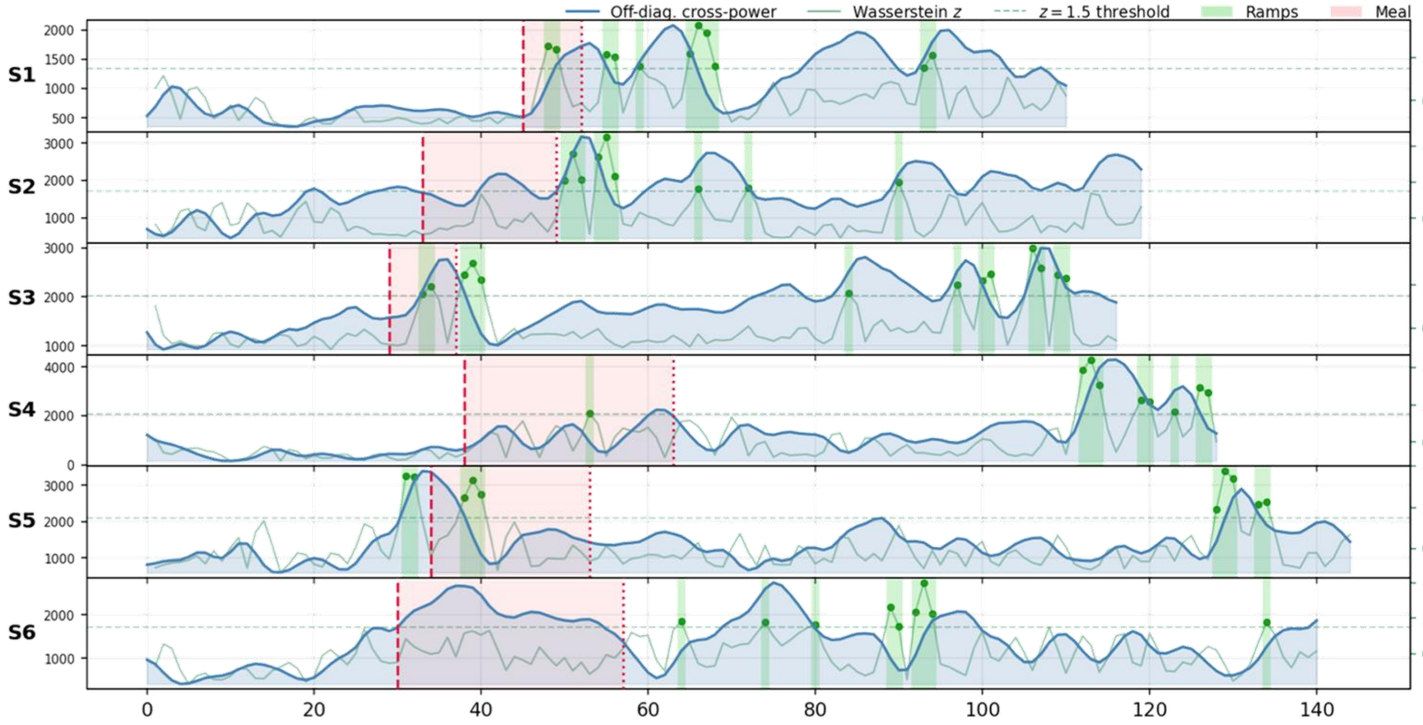
One possible definition of coupling:

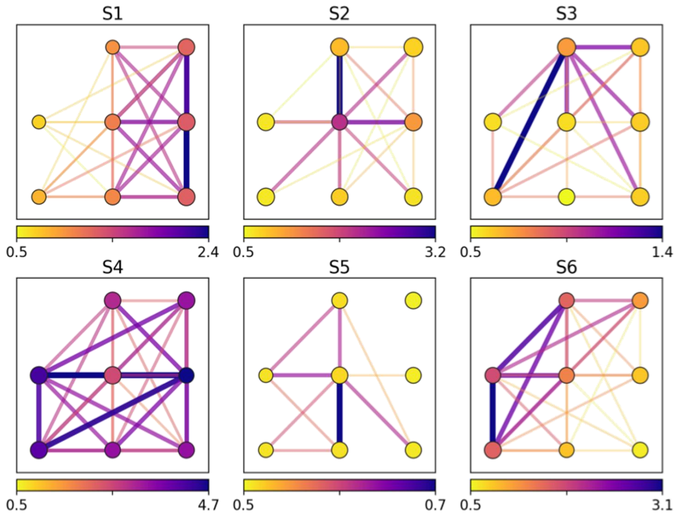
- Cross-power changes over time (shared power in specific frequency bands over time between two signals)

Wasserstein distance of cross-power over time to identify periods of rapid change (e.g. “ramp-ups”)

Spatial map of greatest increases pre- to post-meal per subject

Interesting observations, but how do we tie it to mechanism?



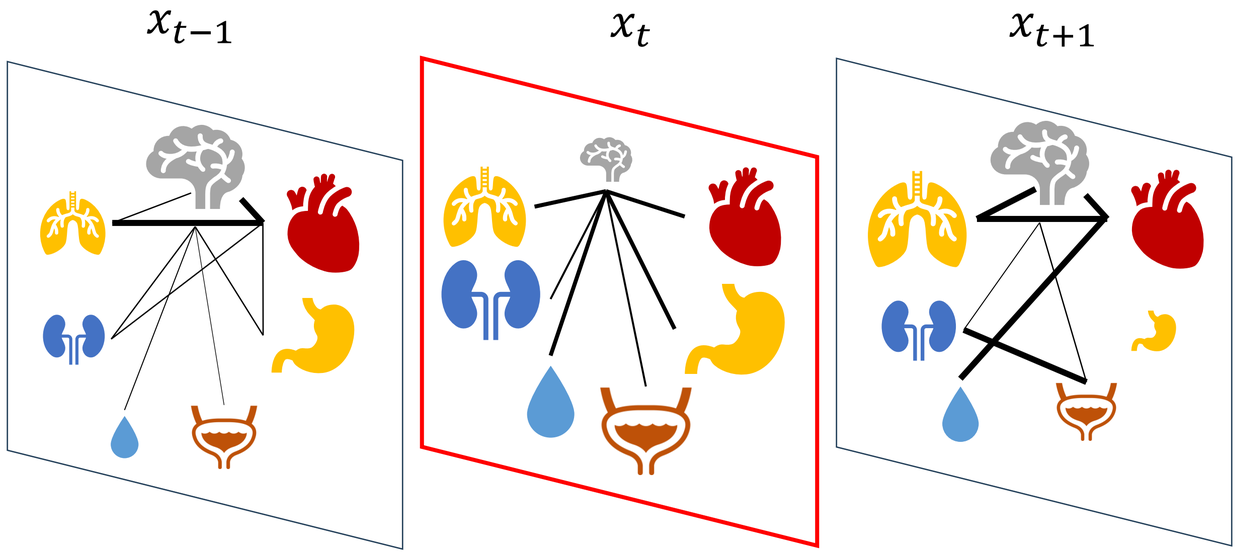




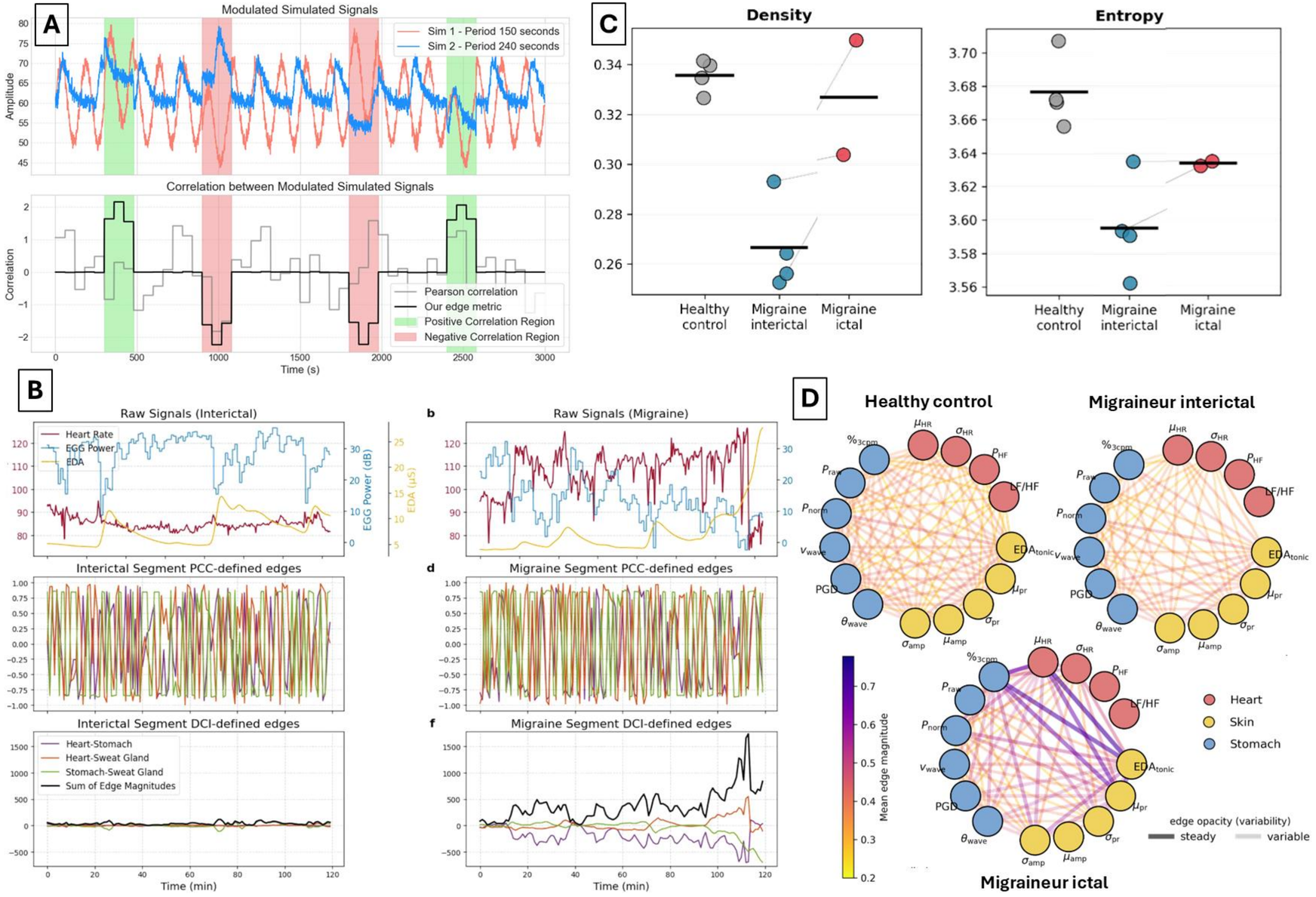
Everts et al. *IEEE BSN.* 2026

Defining the multi-organ autonomic network

- All the major organ systems in the body are functionally connected to each other through the ANS
- This network is dynamic in state and strength, modulated by state and disease
- Each organ system “speaks its own language”
- Like in a social network, an organ can change in importance over time



More multimodal modeling applications



Mohan et al. *SfN* 2025
Mohan et al. *IEEE BSN 2026*

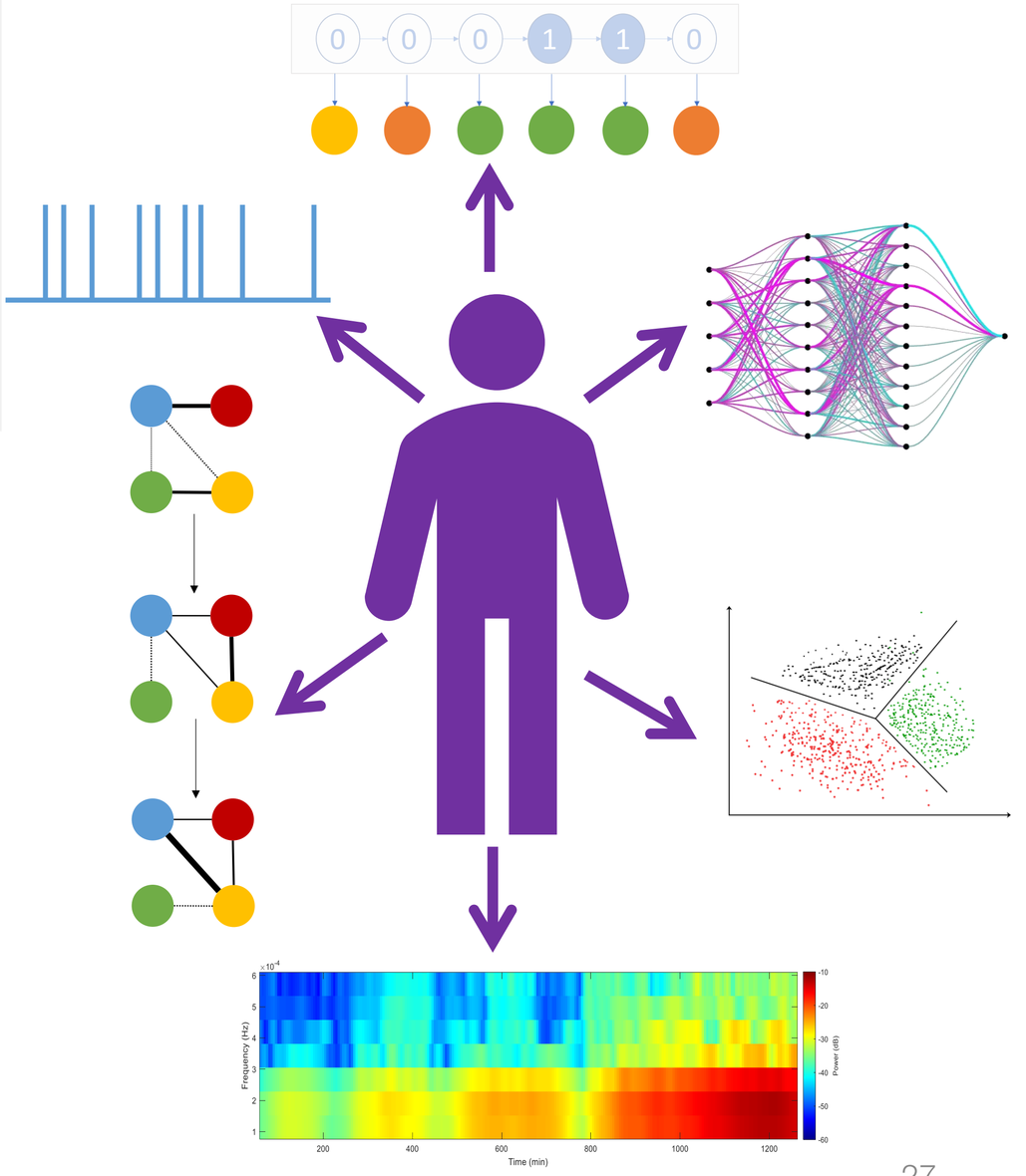


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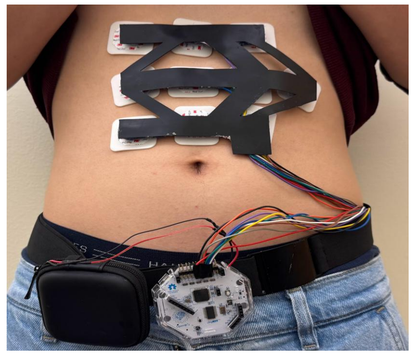
3. Despite being nonlinear and complex, physiological systems often have hidden low-dimensionality



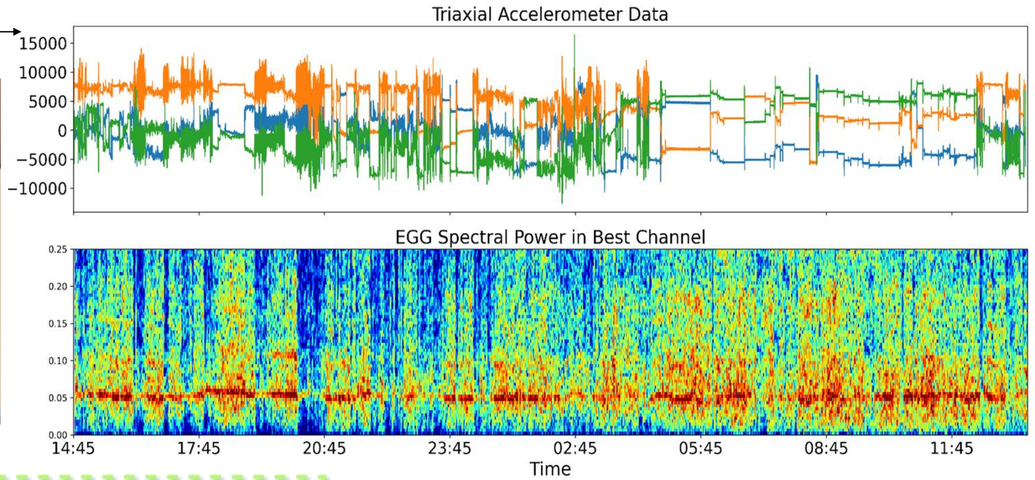
Ongoing hardware development to improve data acquisition

Data acquisition | Organ-level modeling | Multi-organ fusion

A

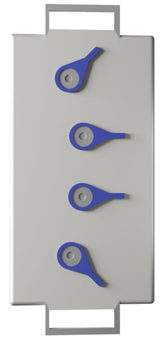


B



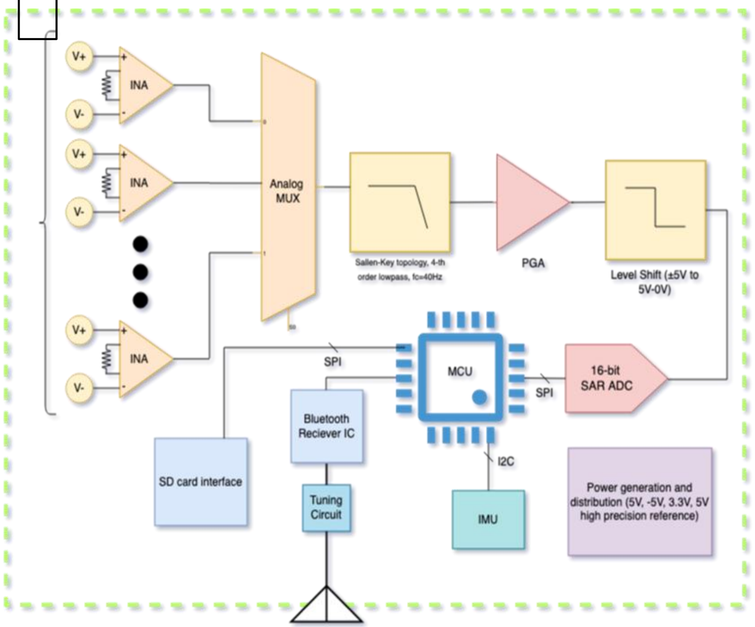
C

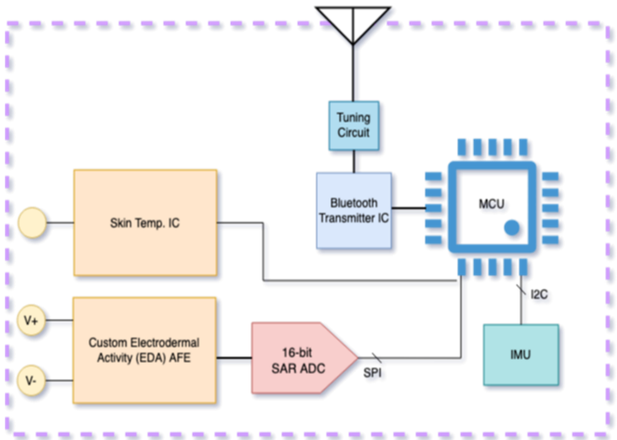


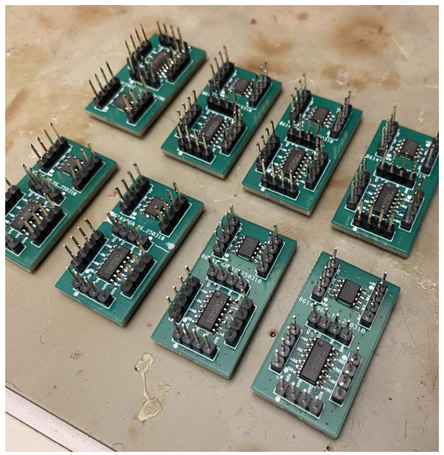


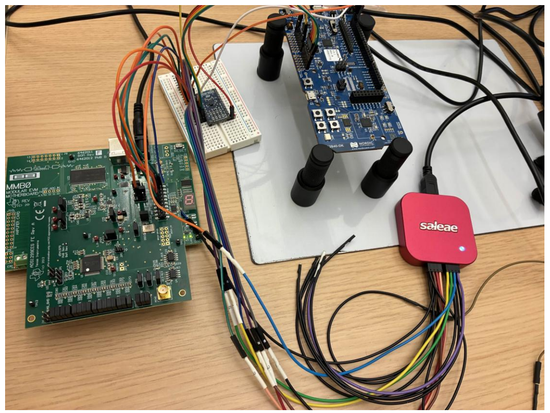


D









Wang et al. *IEEE EMBC* 2025

Spectrum of impacts

PHYSIOLOGY-INFORMED AI

New insights about physiology and disease

Clinical decision support

Personalized prediction and closed-loop control

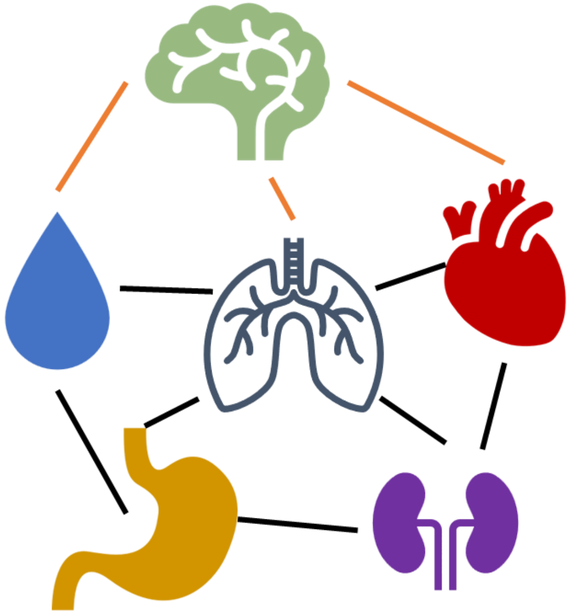
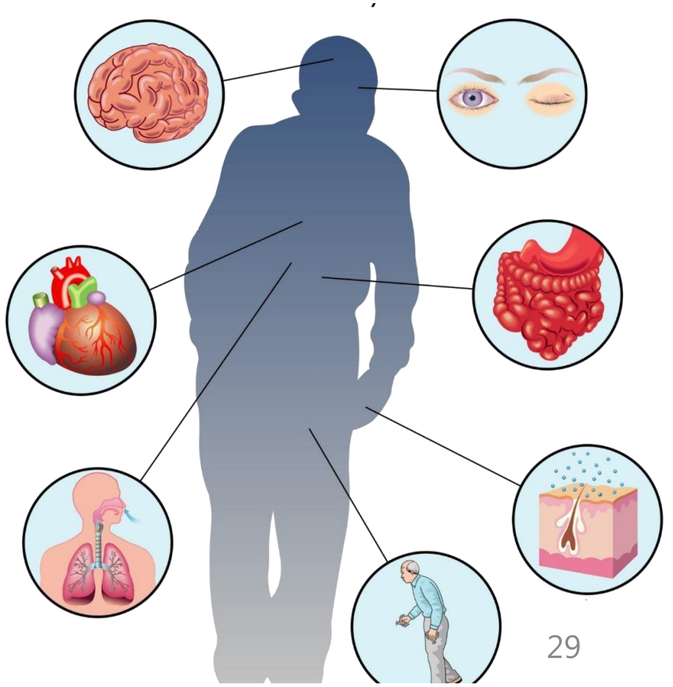




Photo credit: Andrea Piacquadio



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