From Physiological Signals to Systems

Physiology-Centred Hybrid AI for Personalized Digital Health

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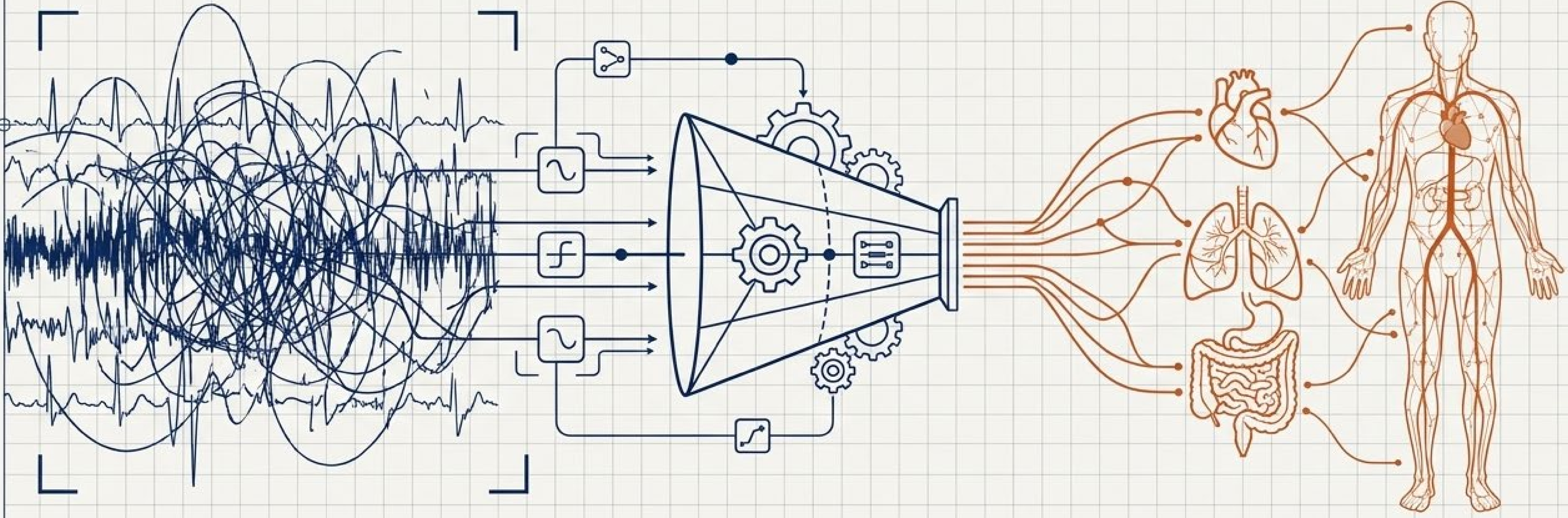
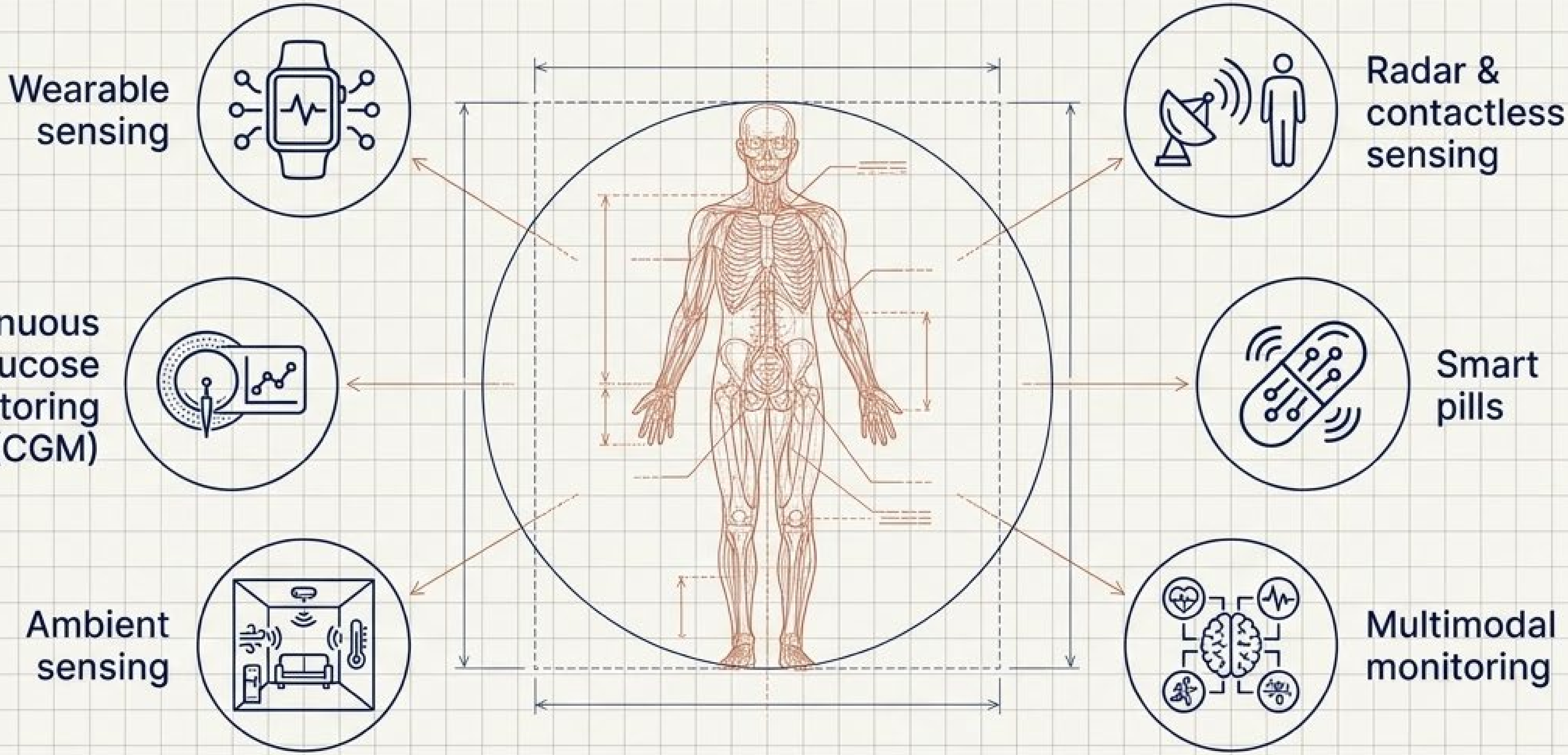
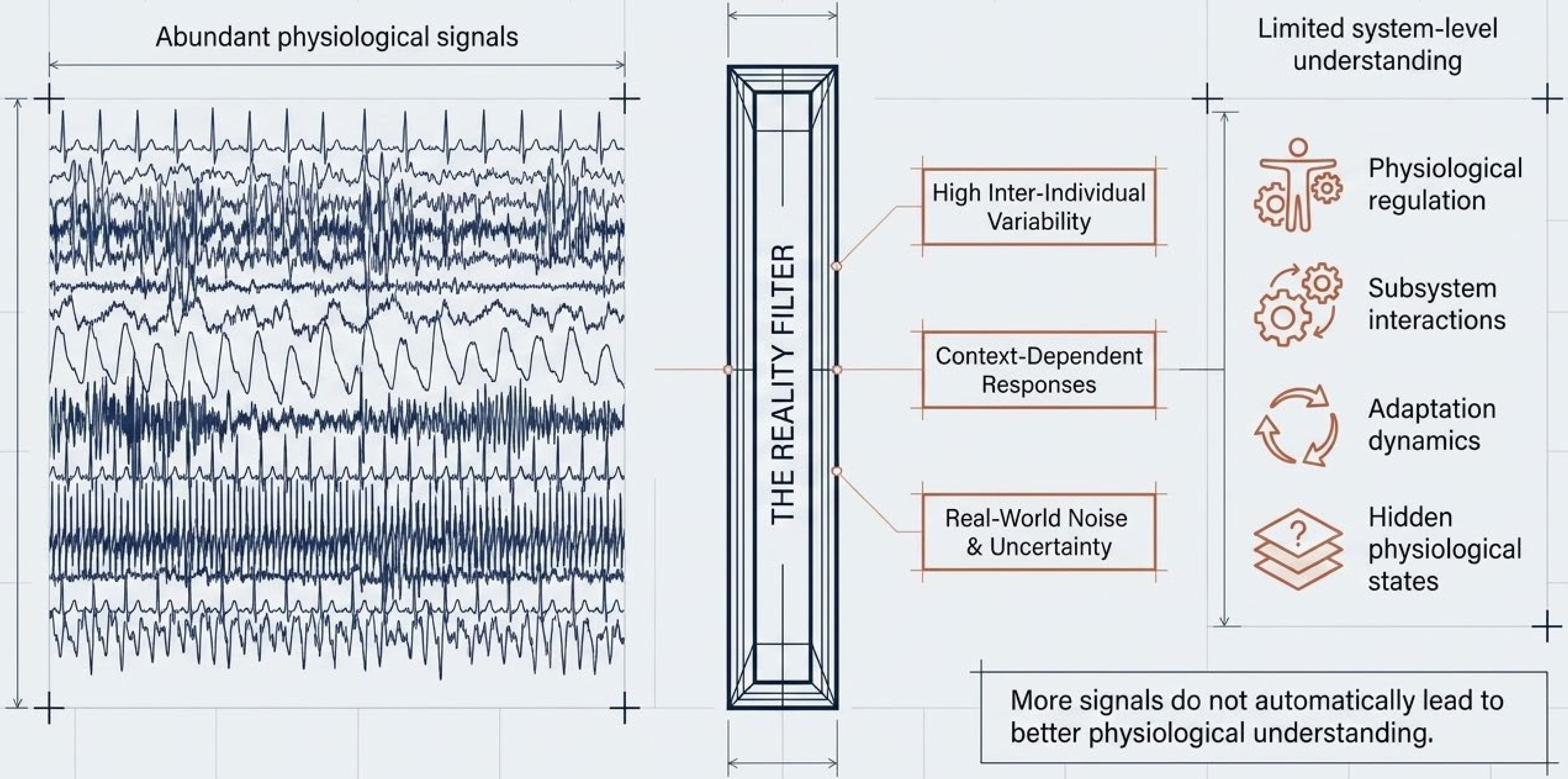


We Can Measure Physiology Everywhere



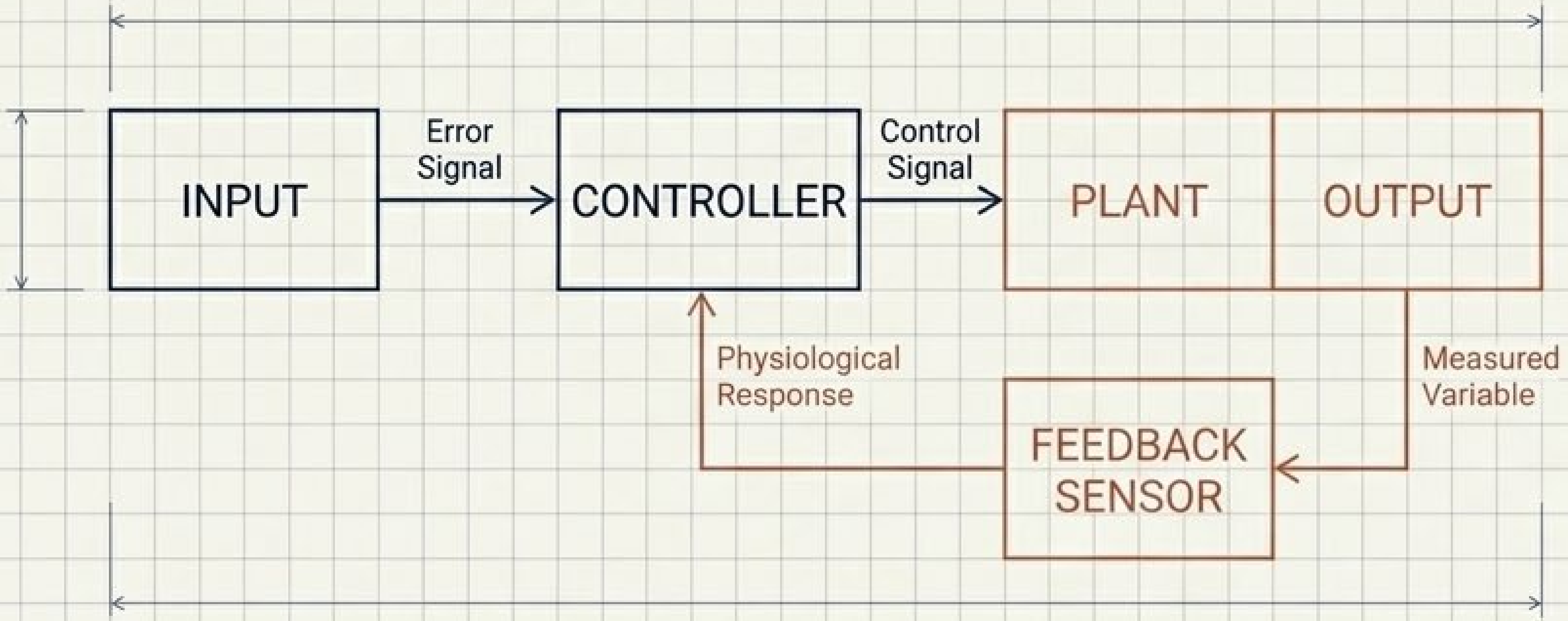
Continuous physiological information can now be collected at an unprecedented scale.

The Missing Systems Perspective



Early Physiological Systems Thinking

Core Idea: Physiology originally viewed as a coupled regulatory system governed by feedback and homeostasis. Signals were interpreted as indirect manifestations of hidden regulation.

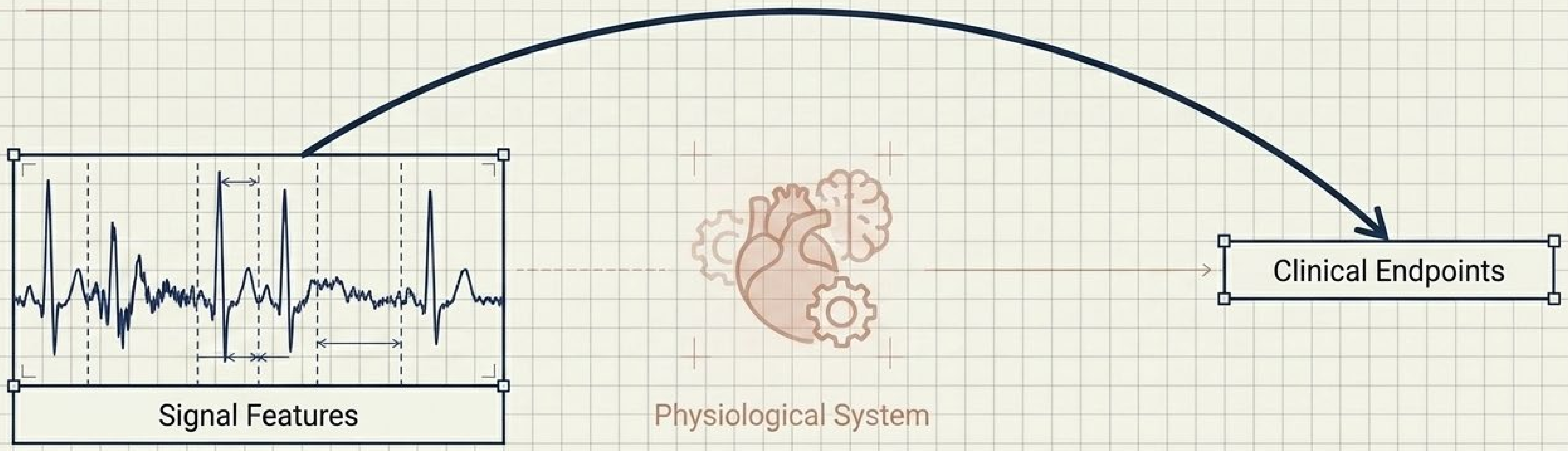


Integration Attempt: Early cybernetics and control physiology attempted to mathematically connect observable dynamics with internal regulation.

Limitation: Physiological systems could be theorised, but not continuously observed.

System-level physiological thinking emerged before sufficient sensing observability existed.

The Rise of Biomedical Signal Processing



Core Idea: As digital sensors emerged, the focus shifted to extracting statistical and morphological features from isolated signal streams.

Integration Attempt: Automated diagnostics and early machine learning linked signal features directly to clinical endpoints.

Limitation: The physiological system was bypassed. Signals were treated as mathematical sequences rather than outputs of interacting biological systems.

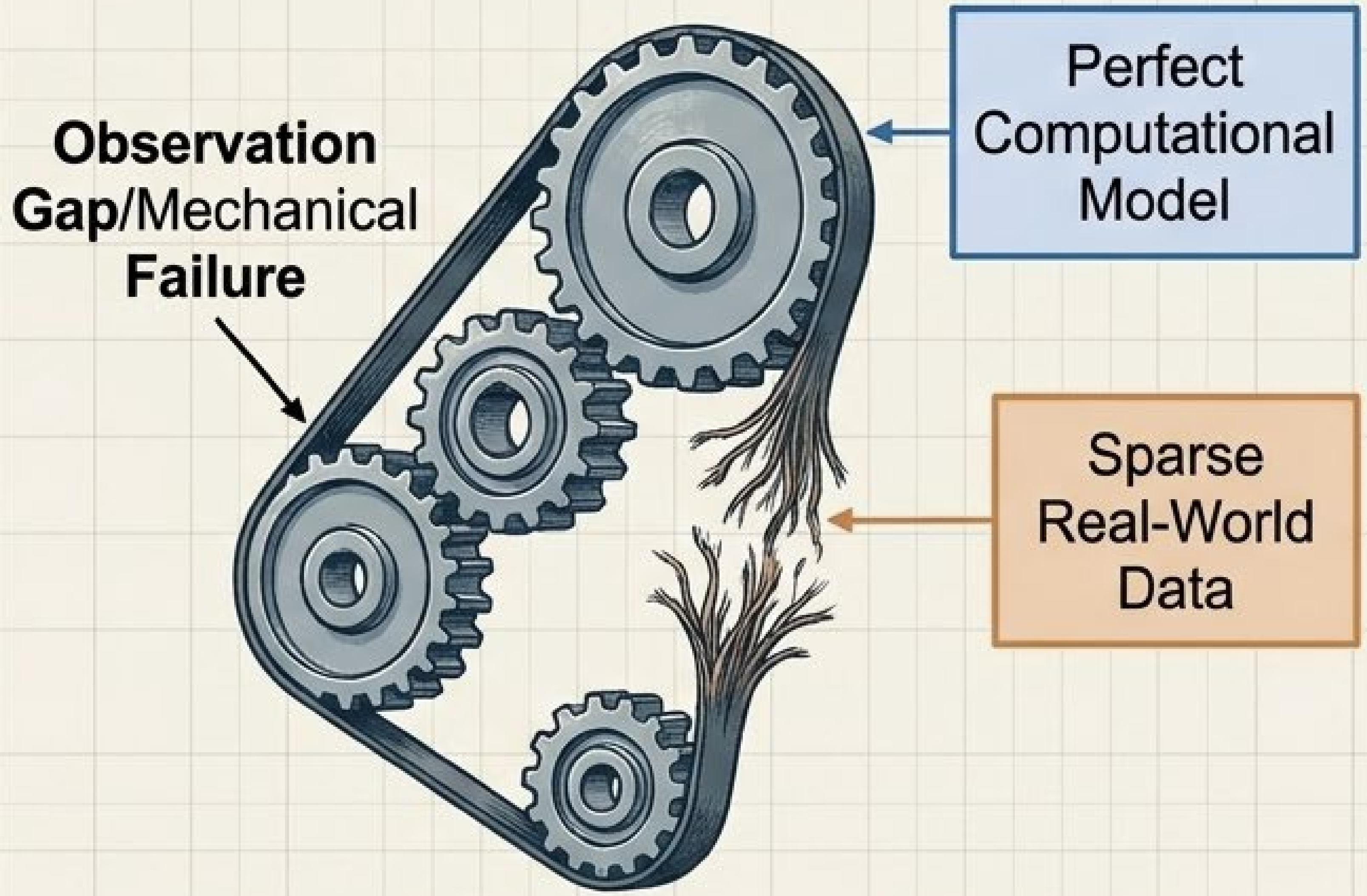
Physiological observability improved, but signals and systems became increasingly separated.

Toward Computational Physiological Inference

Core Idea: Physiological systems increasingly modelled as hidden dynamical processes underlying observable measurements.

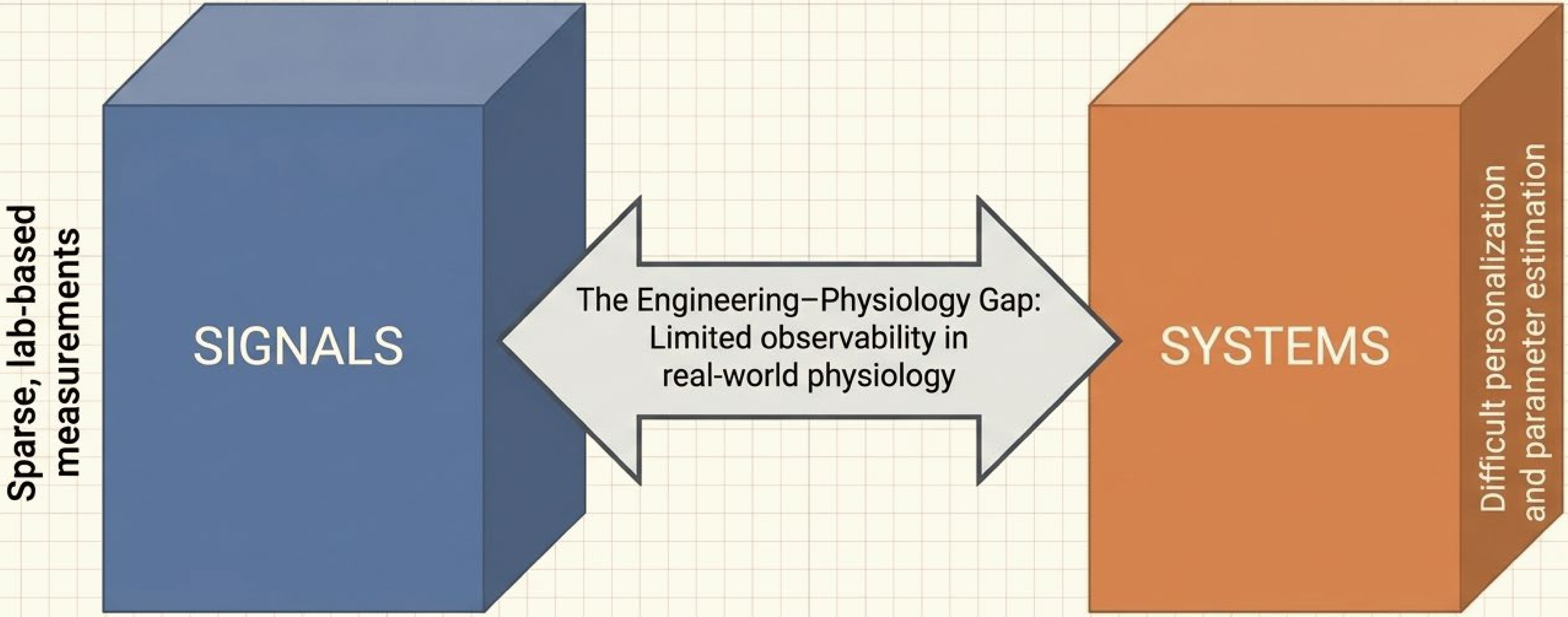
Integration Attempt: State-space modelling, Kalman filtering, and computational physiology attempted to reconstruct internal states from partial observations.

Limitation: Mechanistic complexity exceeded practical sensing capability.



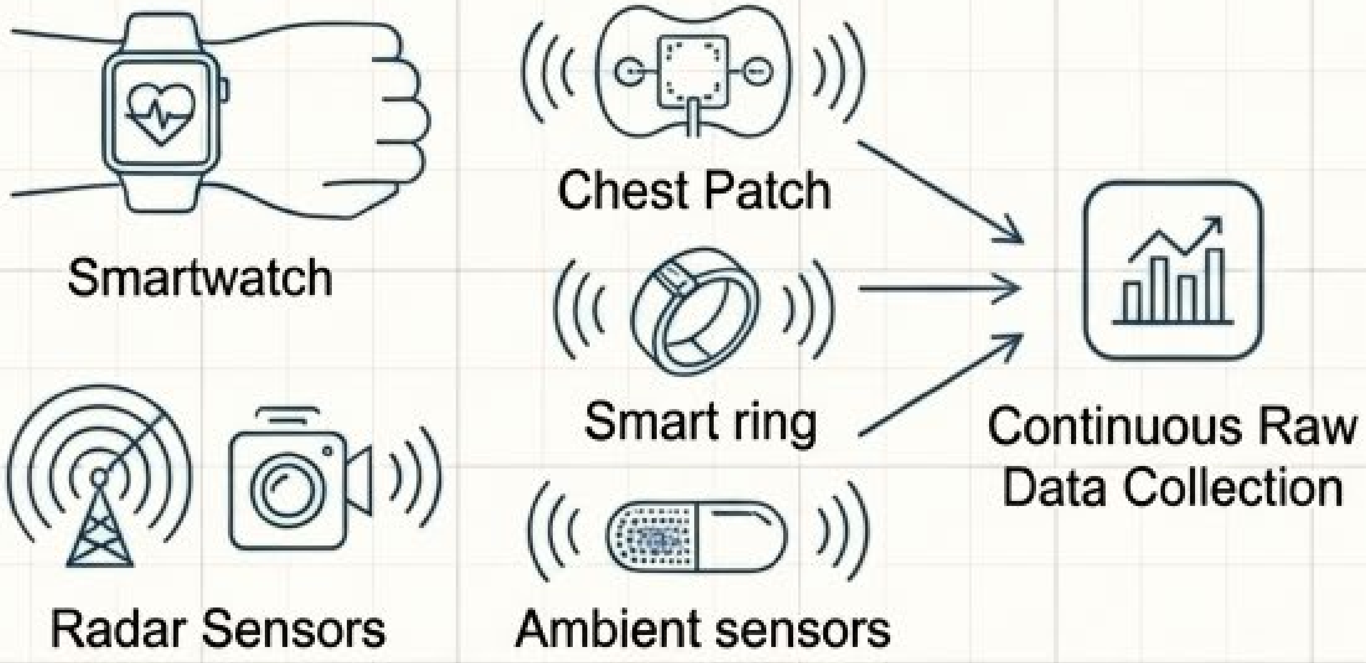
Physiological systems remained only partially observable. Reconstructing physiology increasingly became a computational inference problem.

Why Signals and Systems Never Fully Merged



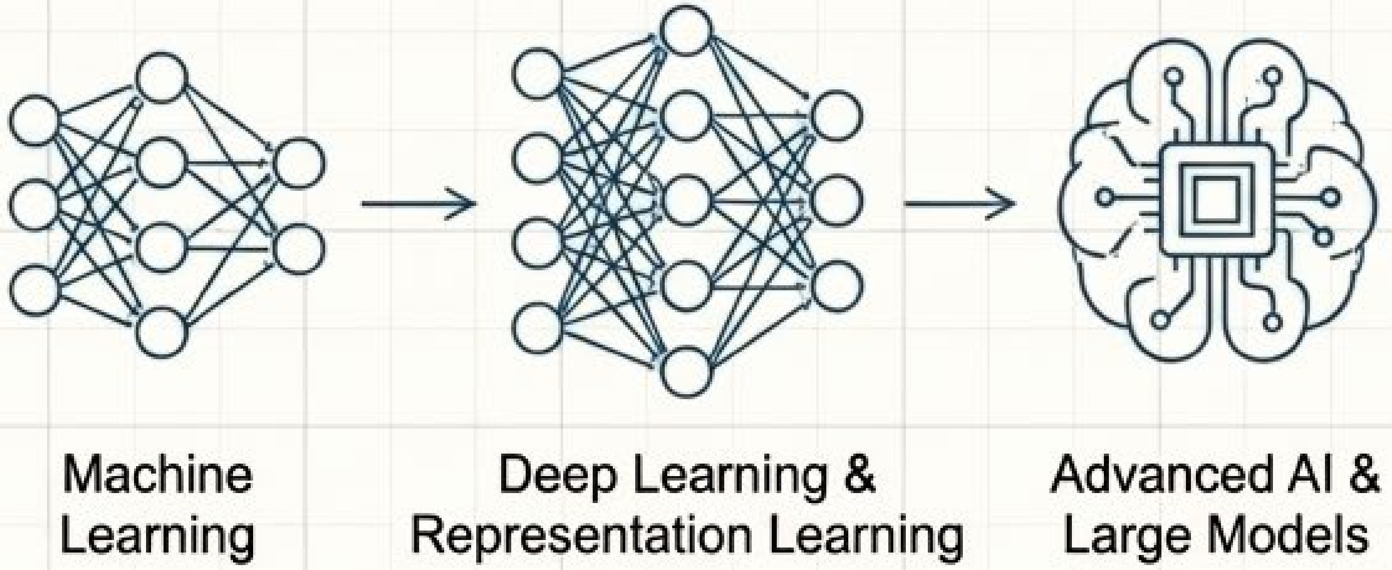
Advances in Physiological Sensing and AI

Multimodal Physiological Sensing in the Real World



Wearables, Ambient, Contactless, Continuous Data.

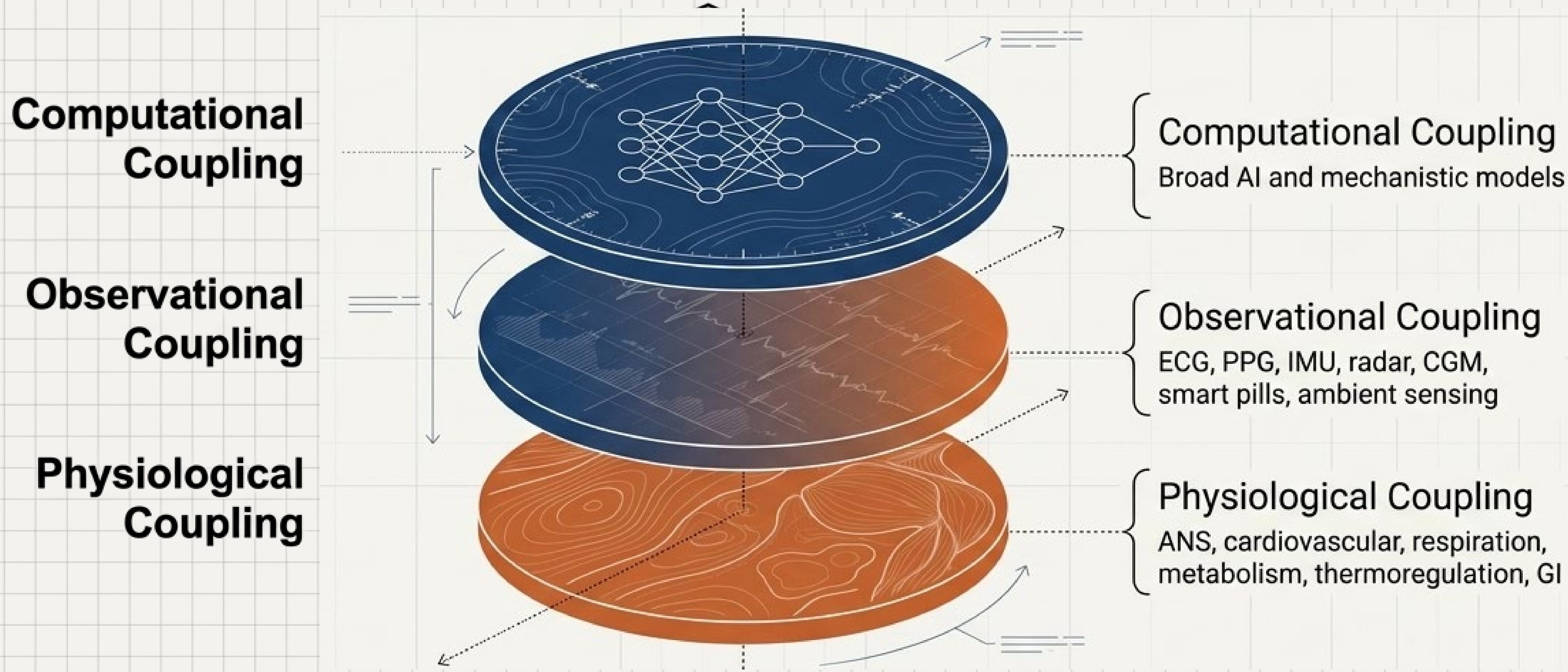
The Booming Development of AI



Edge Computing, Deep Learning, Representation Learning, Large Models.

These two contextual factors created favorable conditions for signal and system integration.

Coupled Physiological Systems Under Partial Observations



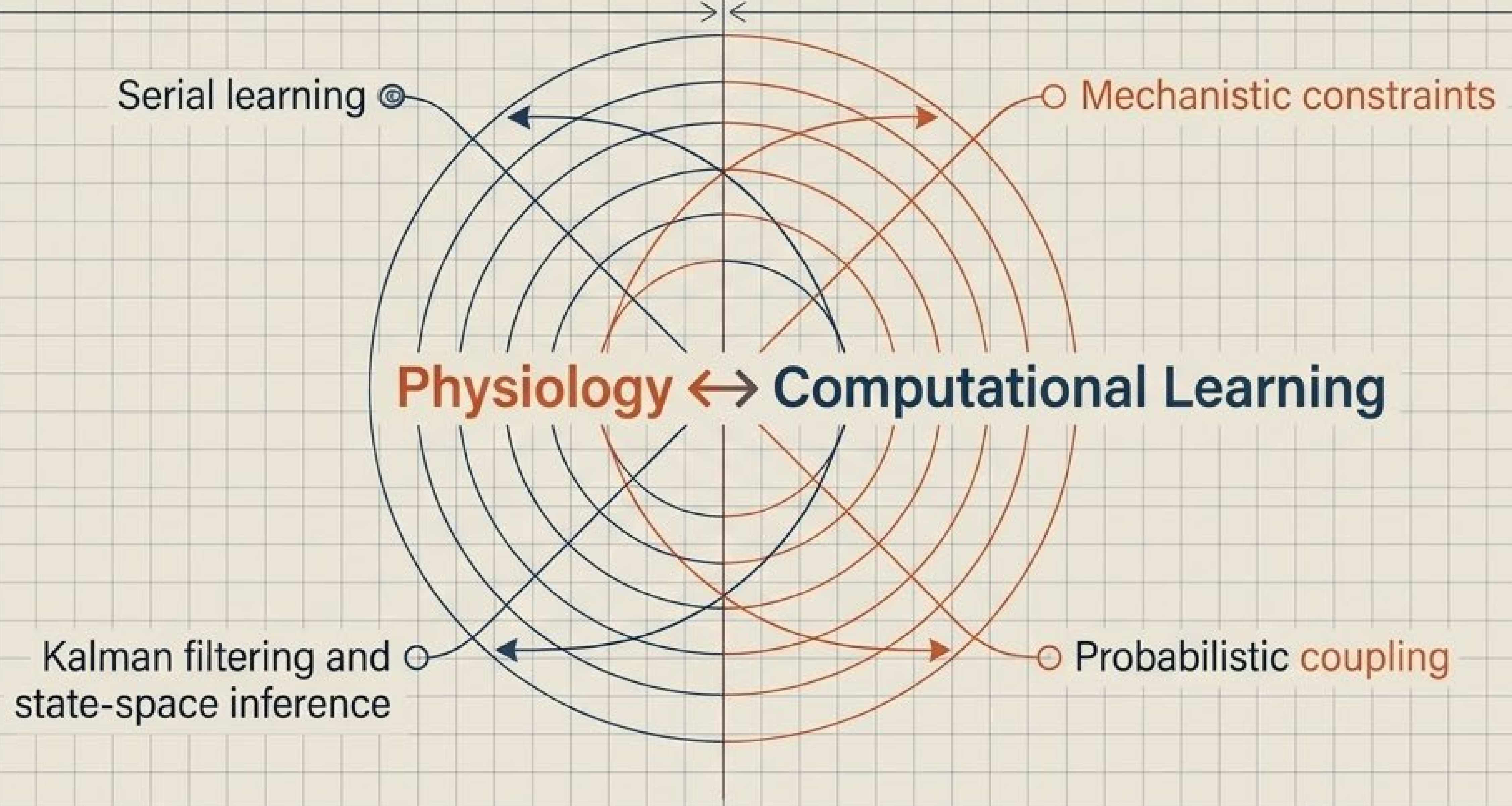
Signal coupling originates from underlying physiological coupling, and understanding these interactions requires computational coupling beyond isolated signal analysis.

Why Coupling Matters

	Pure Mechanistic Models	Pure Data-Driven AI	Hybrid AI
Interpretability	High	Low / Black Box	High
Real-World Adaptability	Low	High	High
Complexity Handling	Struggles with noise	Struggles with meaning	Integrates both perfectly

Physiological models provide structure. Data-driven AI provides flexibility. Hybrid AI handles variability, hidden dynamics, and personalization.

Computational Coupling in Hybrid AI

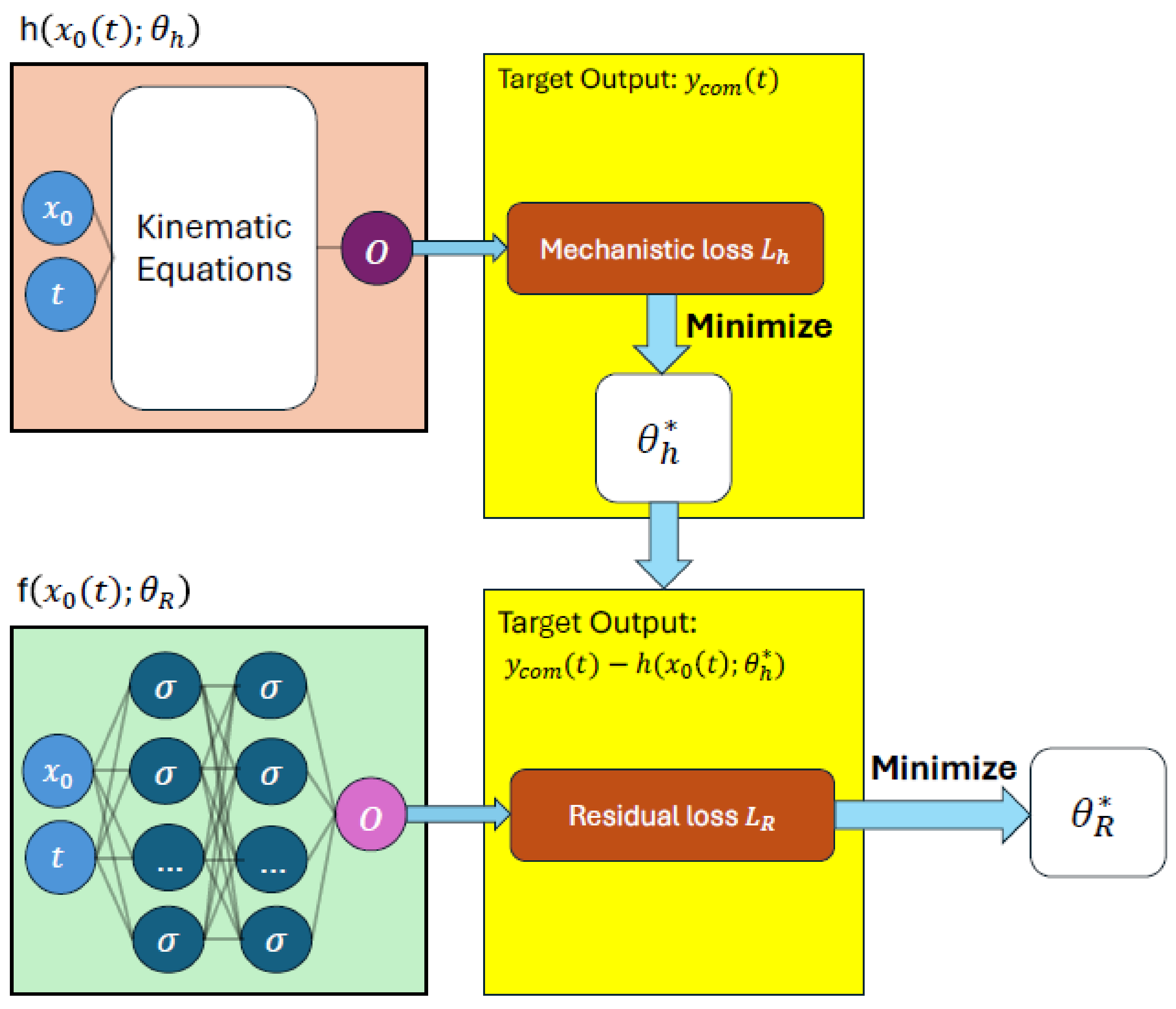


Hybrid AI is not a single methodology, but multiple ways of integrating physiological structure into the learning process itself. The key question is not only how to learn from physiological data, but how physiological structure interacts with computational learning.

Example I: Serial Learning

Body Centre of Mass (COM) dynamics from wrist-worn sensors.

Description: Utilizing a simplified Kinematic Model (KM) to map wrist IMU signals to COM acceleration, followed by Neural Network (NN) components to learn residual nonlinearities.

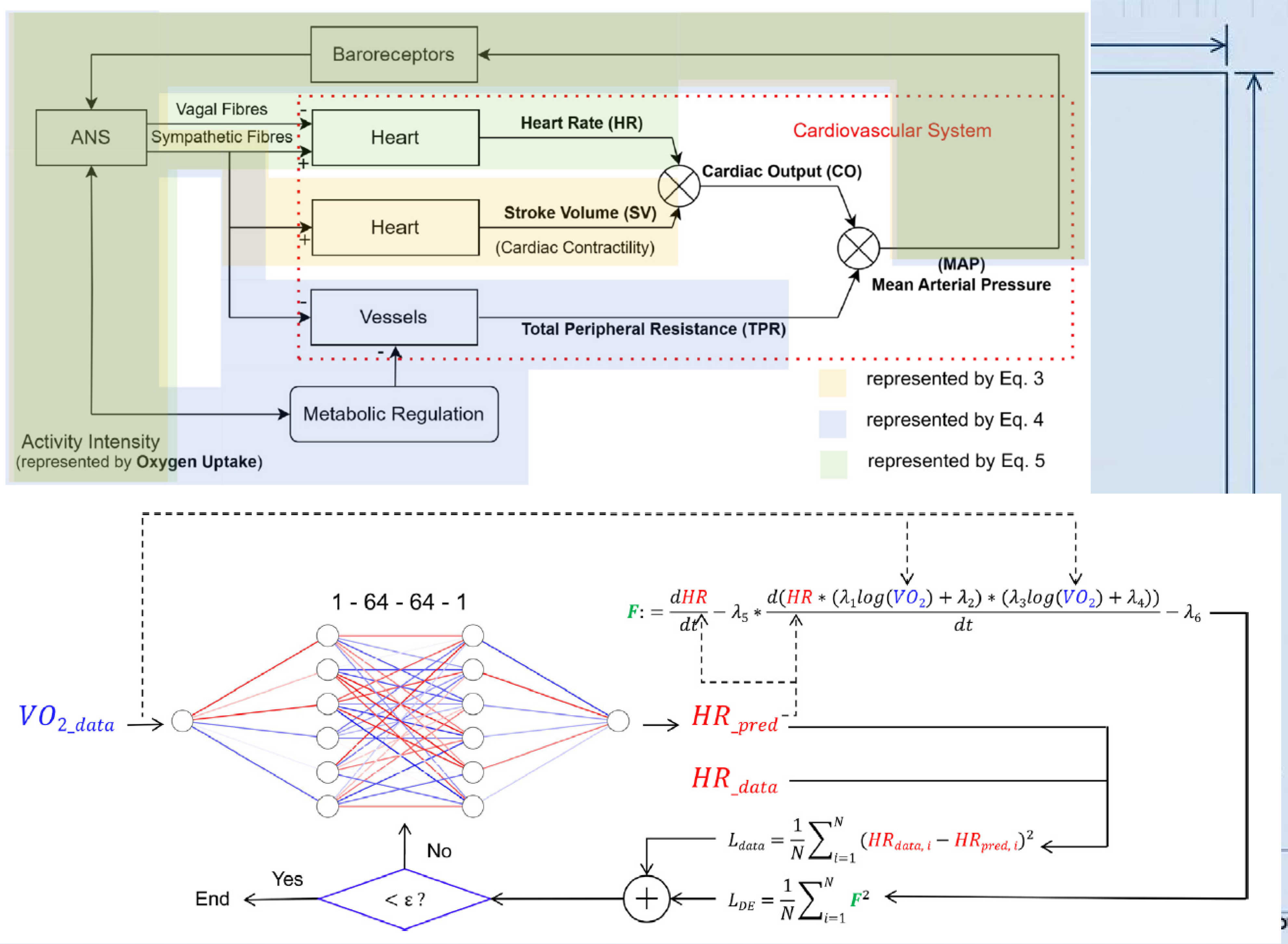


5.3% to 9.3% normalized errors for gait activities, 3.9% for the sit-standing activity.

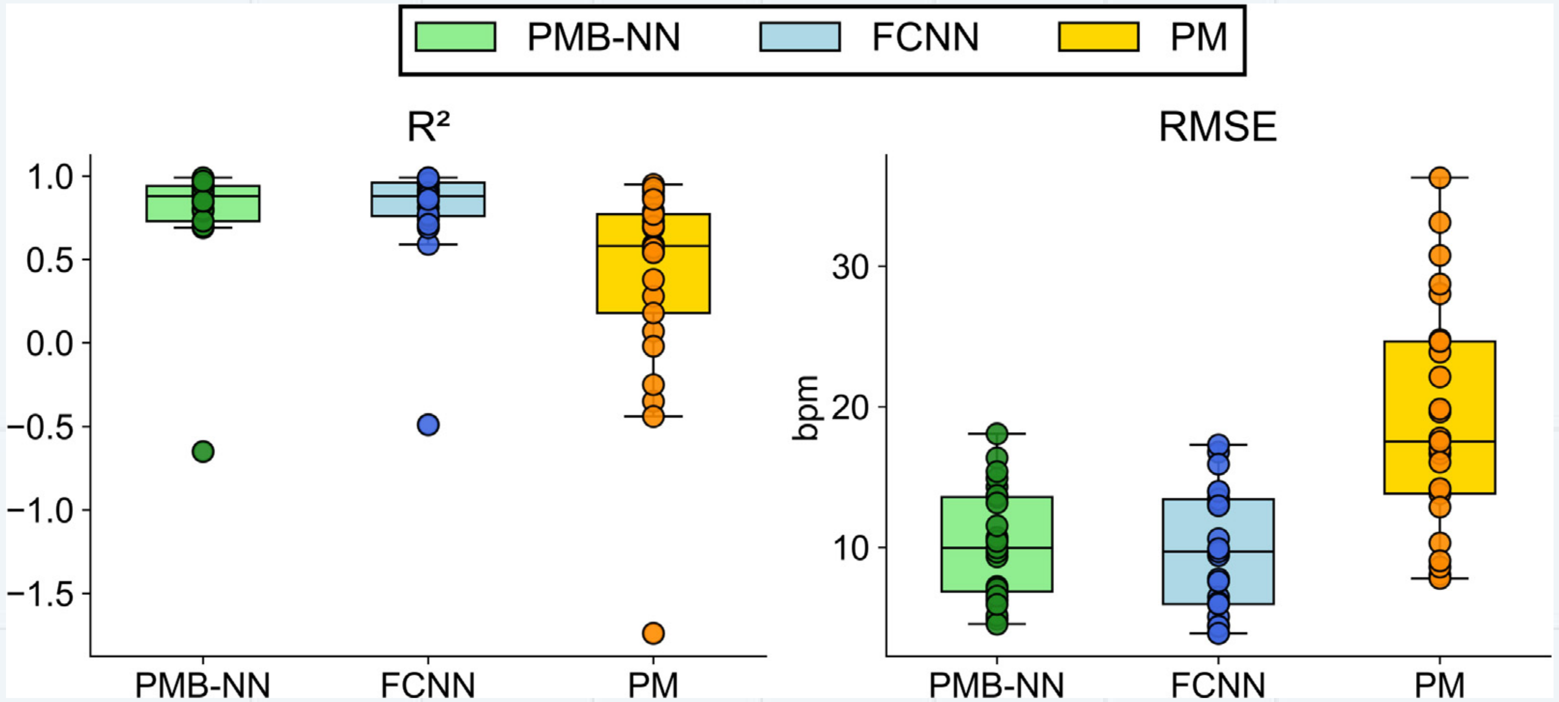
Example II: Mechanistic Constraints

PMB-NN for the metabolic–heart rate relationship.

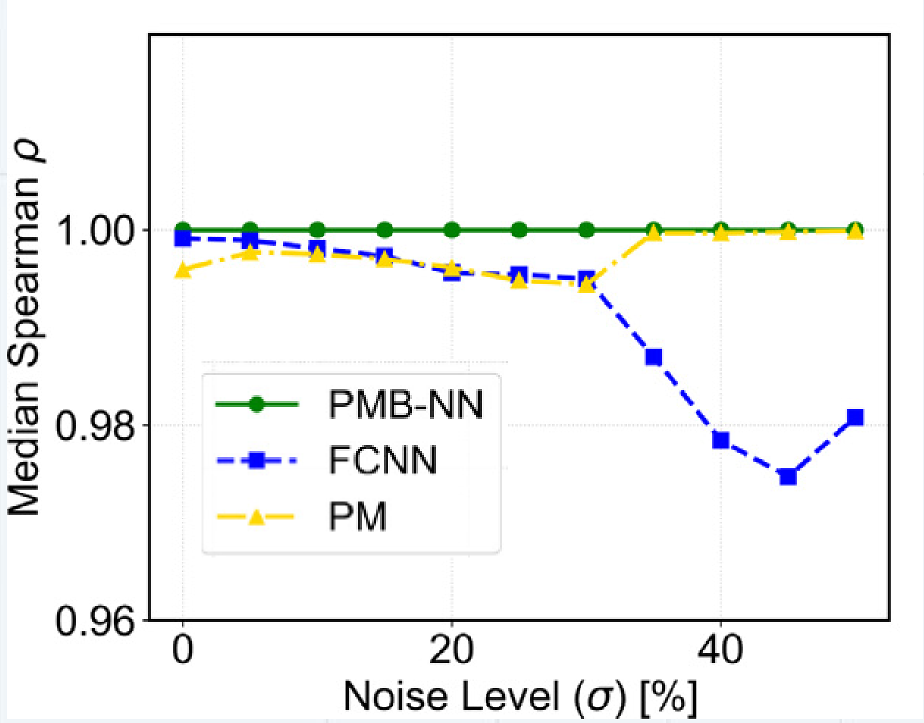
Description:
Embedding explicit physiological equations—such as Stroke Volume (SV) and Total Peripheral Resistance (TPR) functions—directly into Neural Network training as a mechanistic loss penalty.

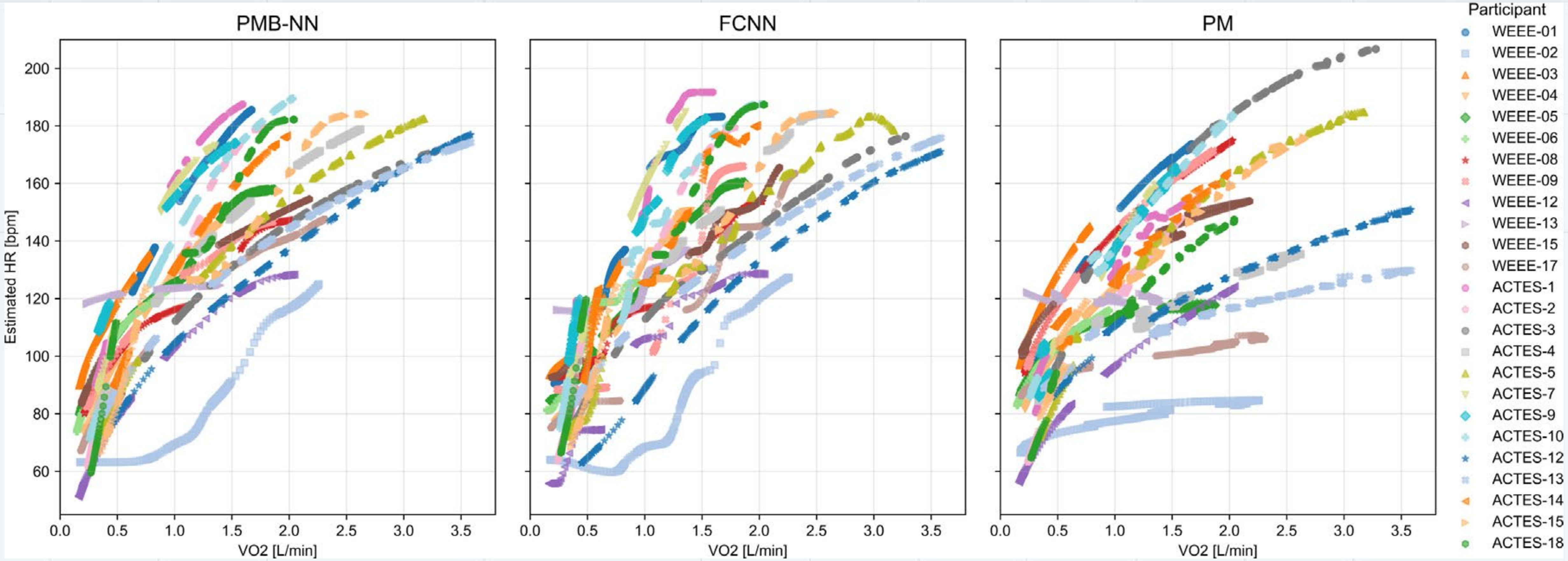


- Performance PMB-NN ≈ FCNN, PMB-NN >PM.
- Plausibility for HR-$\dot{V}$ O2 coupling: PMB-NN > FCNN, PMB-NN >PM.
- PMB-NN shows interpretability with identifying personalized parameters of the PM.



Physiological Plausibility Criterion = a smooth, monotonic relationship between HR and VO_2

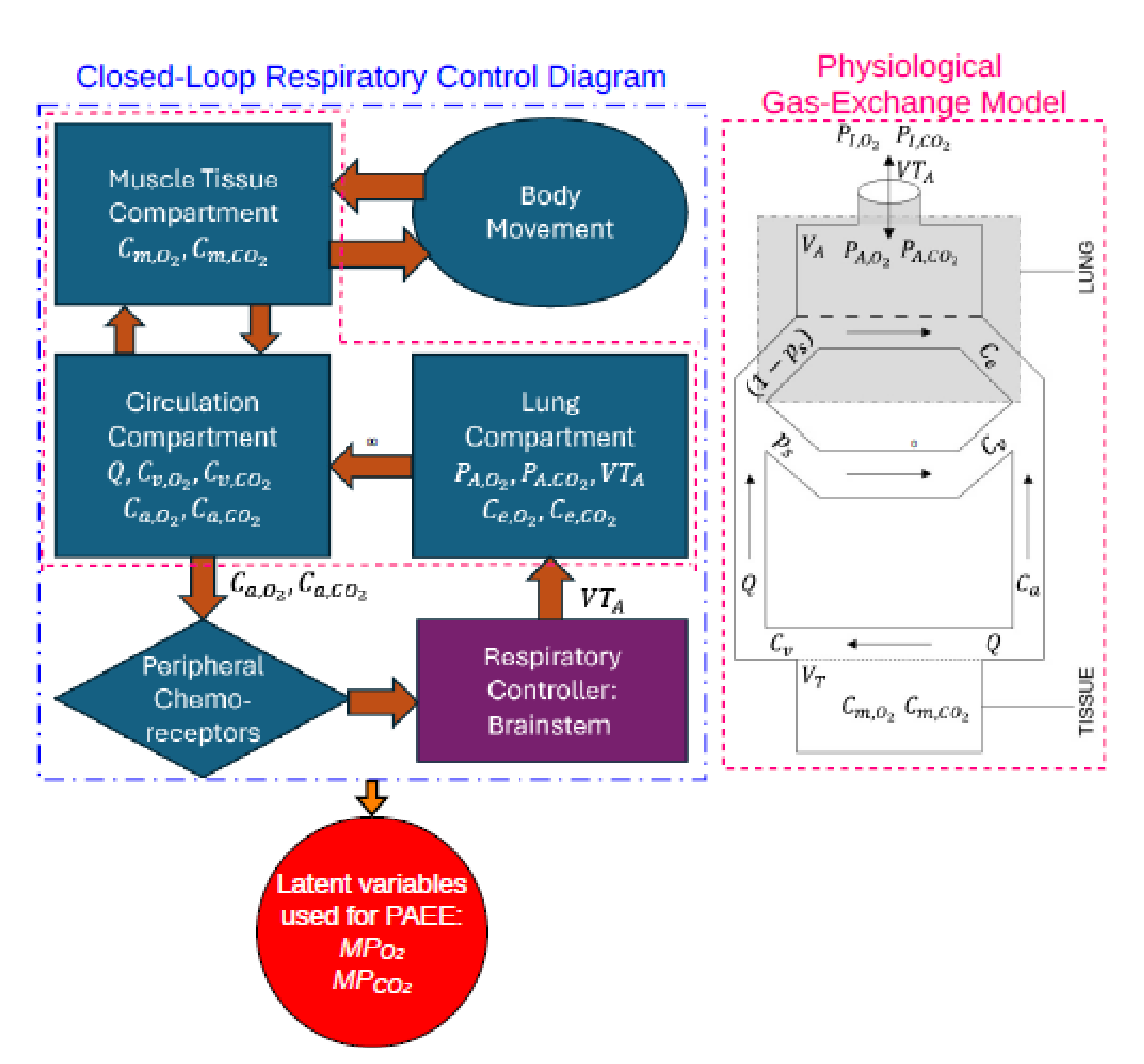




Example III: Kalman Filtering and State-Space Inference

PM-EKF for physical activity energy expenditure (PAEE).

Description: A 3-compartment gas-exchange model integrated with an Extended Kalman Filter (EKF) to adaptively fuse physiological predictions with noisy measurements for latent state inference.

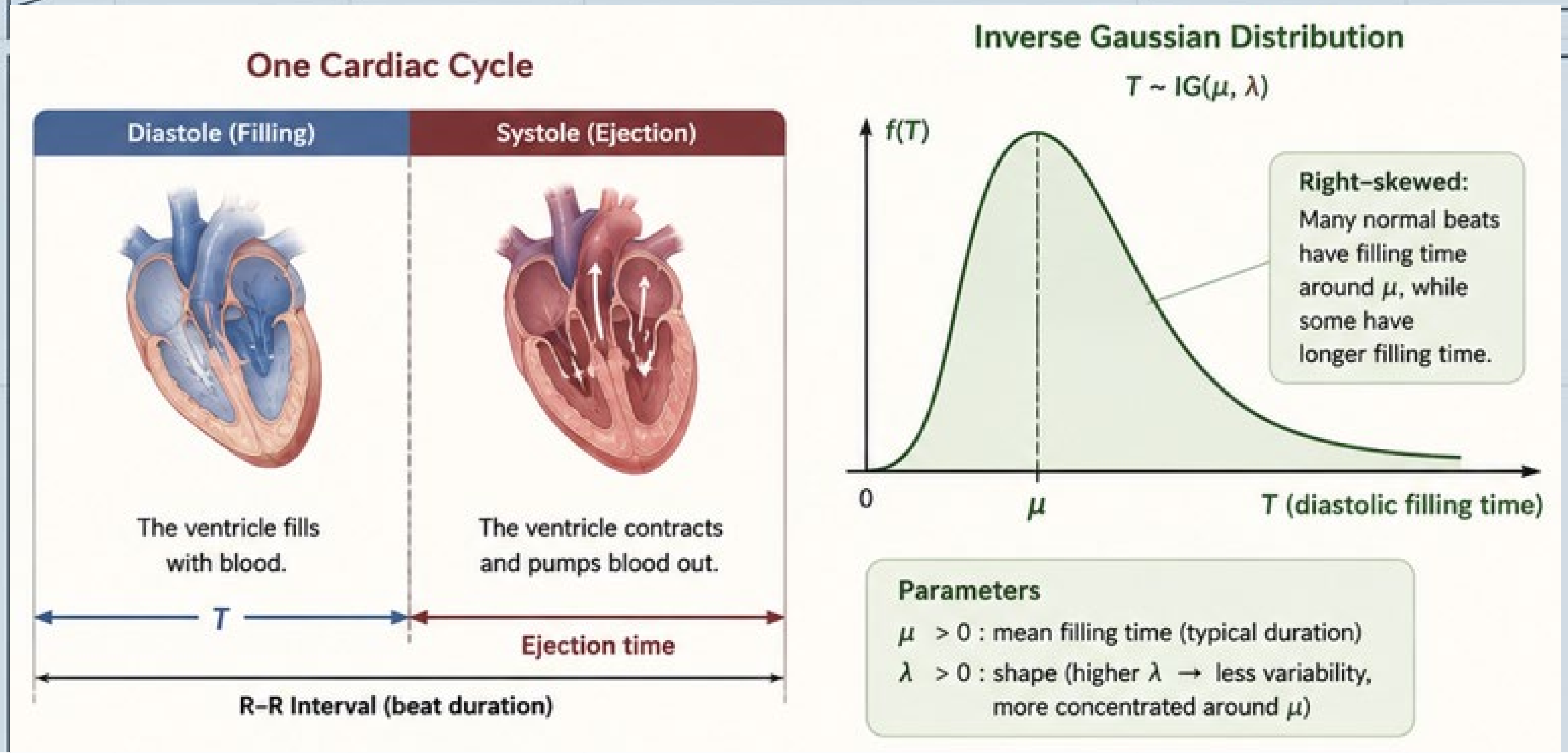


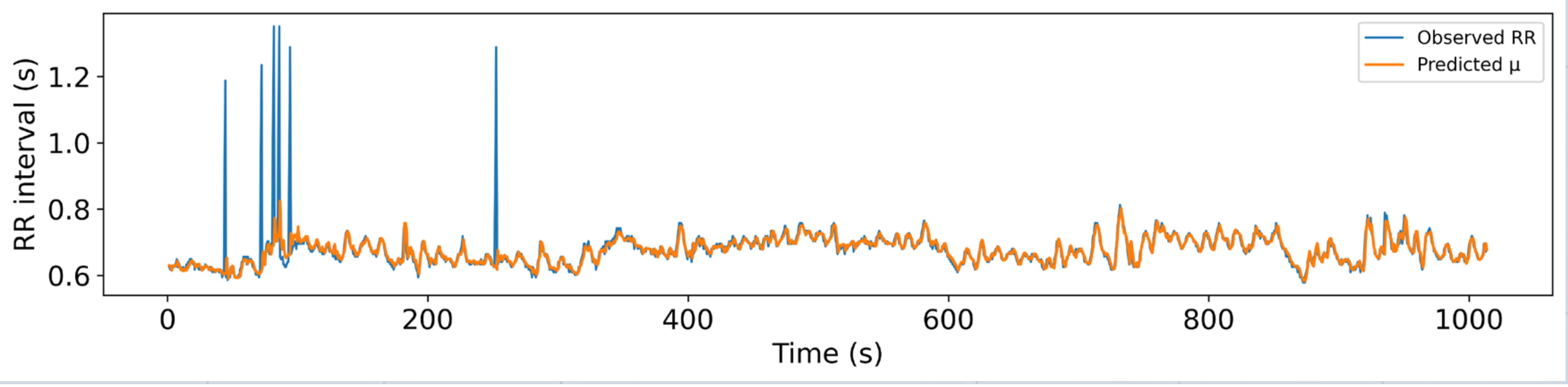
		PM-EKF		CNN-LSTM		LR	
		HR	No HR	HR	No HR	HR	No HR
R^2 Overall	Median	0.72	**0.76**	0.65	0.55	0.52	0.48
	Min–Max	0.60–0.87	0.63–0.81	0.46–0.78	-0.06–0.78	0.23–0.92	-0.00–0.86

Example IV: Probabilistic Coupling

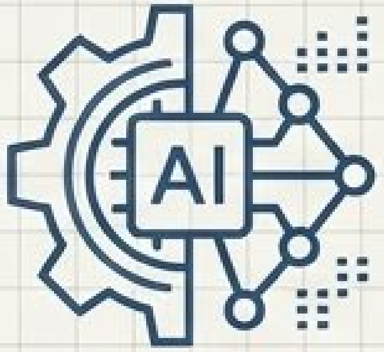
Dynamic Heartbeat Modeling with RNNs and Inverse Gaussian Point Processes (IGP).

Description: Utilizing Recurrent Neural Networks to directly learn and identify the time-varying, time-varying, physiologically relevant IGP parameters governing beat-to-beat R-R interval dynamics.

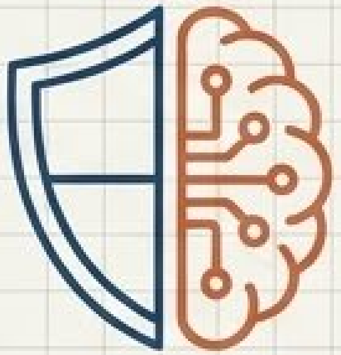




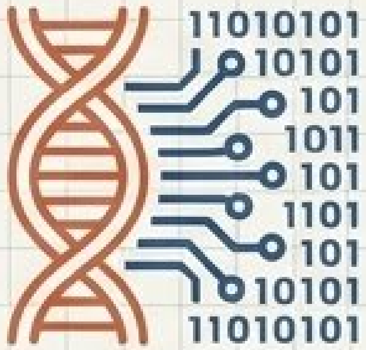
Emerging Scientific Questions



How should physiological and data-driven models interact during learning?



When does mechanistic structure improve robustness, interpretability, or personalization?



Which physiological dynamics should remain mechanistically modelled, and which can be learned from data?

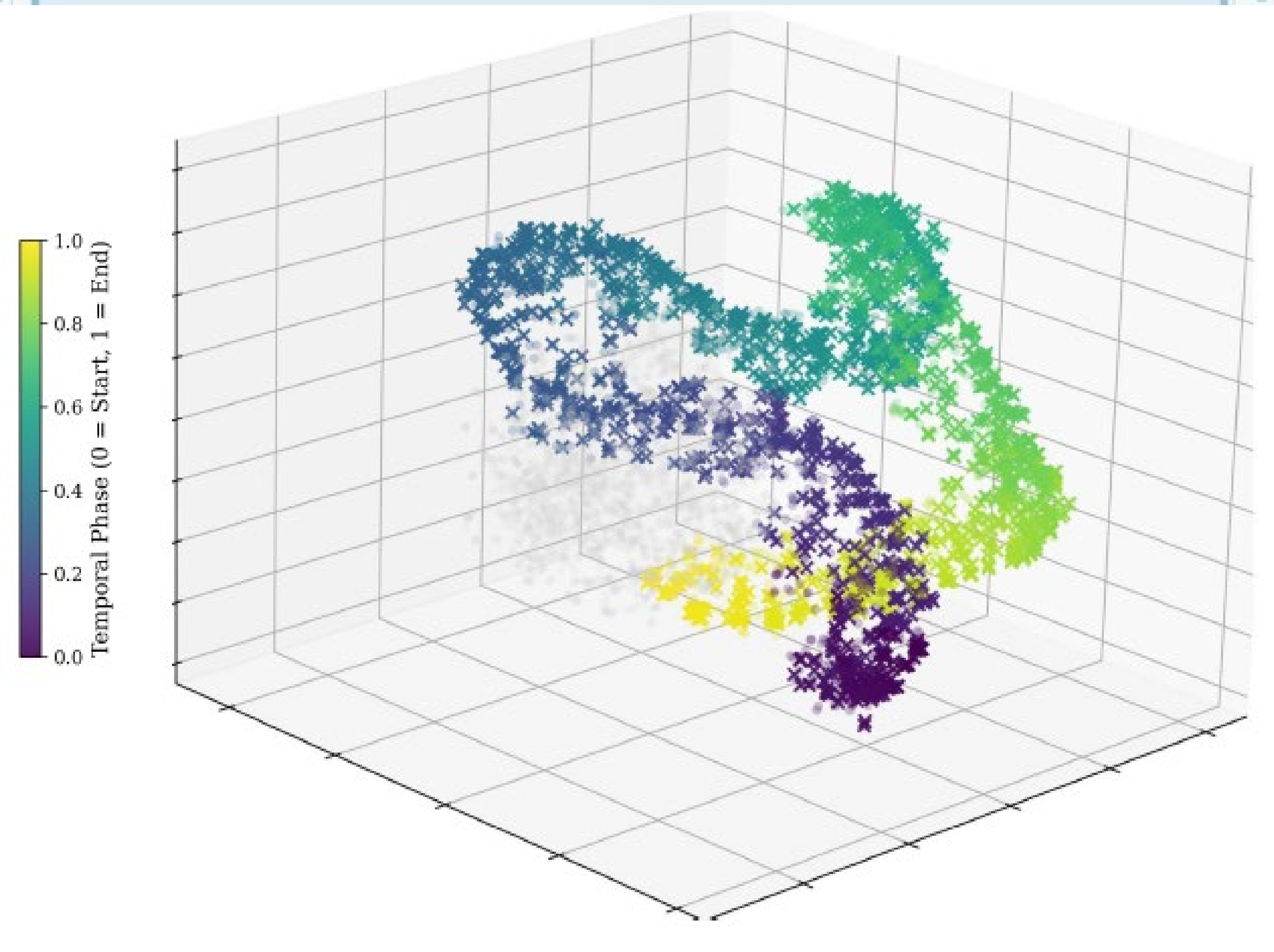
Can computational coupling reveal hidden physiological structure rather than only improve prediction?

Toward Physiologically Structured Representations

Can latent representations capture physiological organization rather than only statistical similarity?

Can multimodal sensing reveal shared latent physiological dynamics?

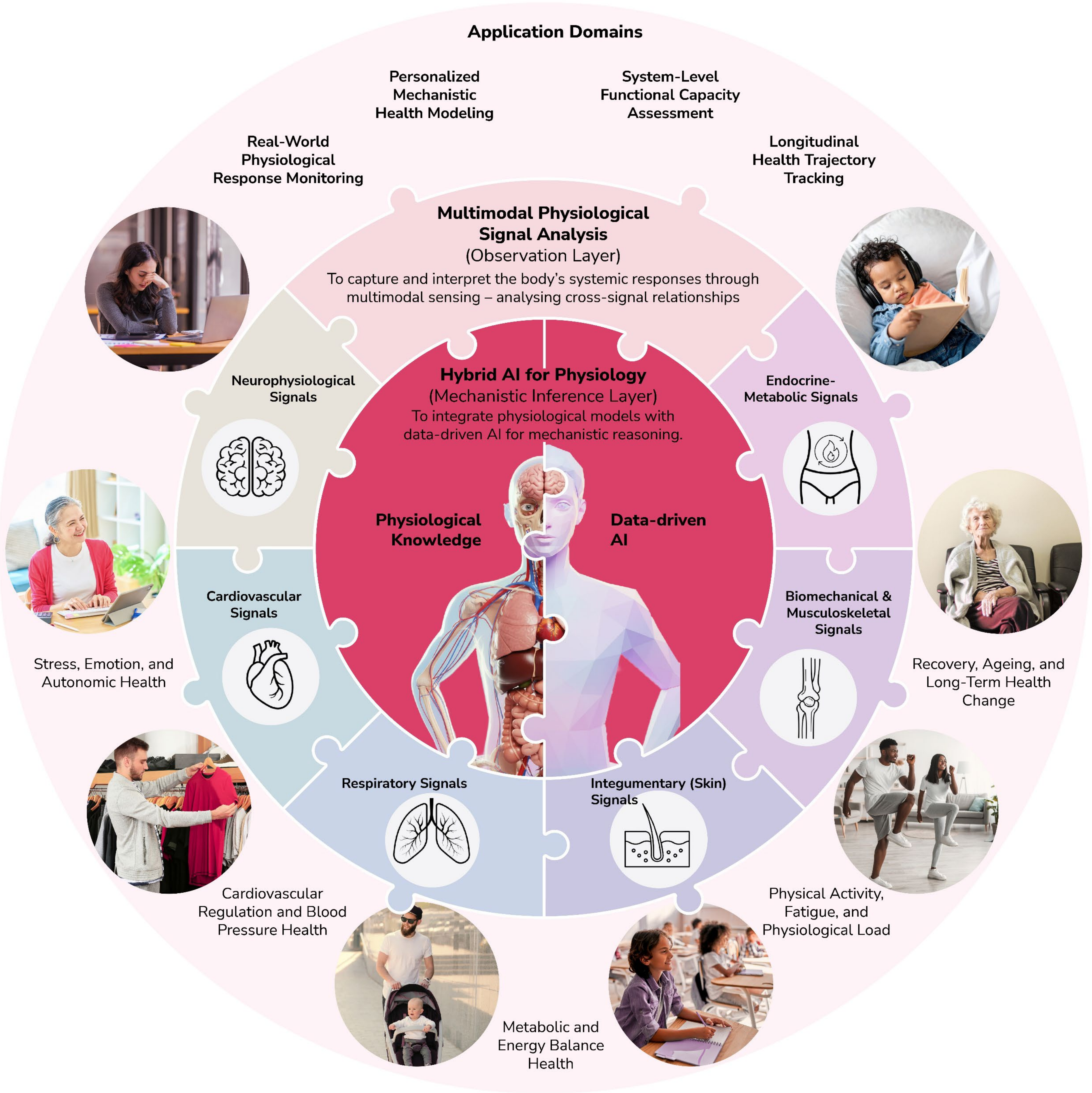
Can physiological structure emerge within representation learning?



From Signals to Systems

Physiological signals and systems are inherently interconnected:

- enabling computational inference from external observations toward hidden system dynamics,
- and ultimately toward deeper understanding of human physiology and health.



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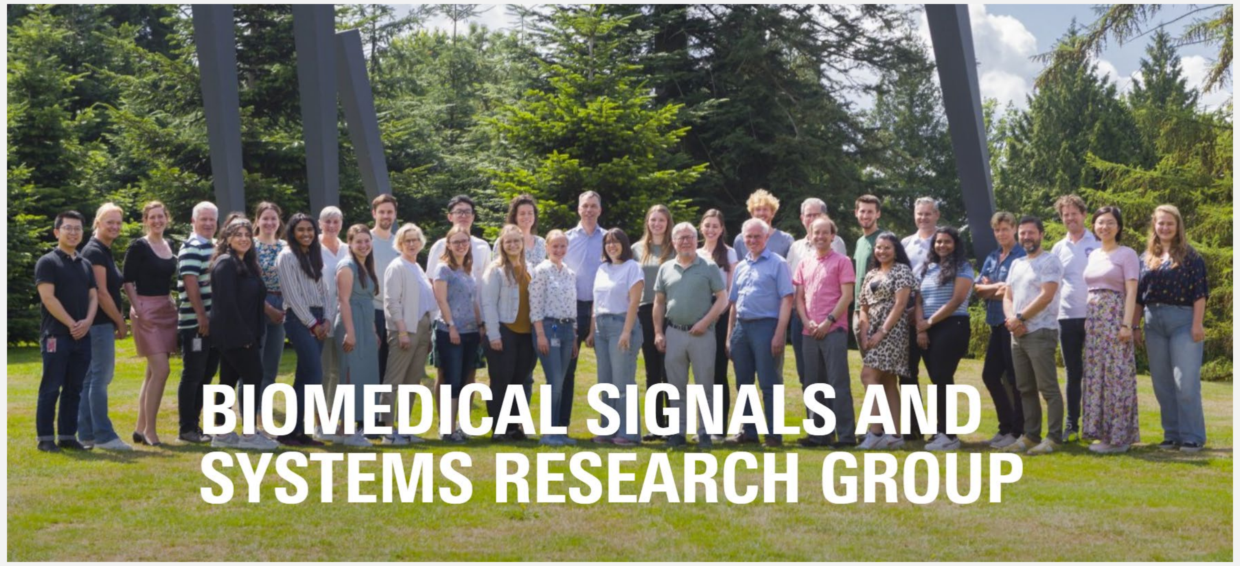

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THANK YOU

From Physiological Signals to Systems

Physiology-centred Hybrid AI
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