Postdoctoral Research Position

Sepsis Prediction by Intelligent Continuous Evaluation (SPICE)
Artificial Intelligence for Continuous Physiological Monitoring in Critical Care

1. Context and Subject

Sepsis remains one of the leading causes of mortality worldwide and a major burden for intensive care units. Despite advances in monitoring, many episodes of hemodynamic deterioration or inappropriate fluid administration remain difficult to predict in real time. Continuous high-frequency physiological signals, including electrocardiography, invasive and non-invasive arterial pressure, plethysmography, and respiratory traces, contain rich yet underexploited information on circulatory responsiveness and impending instability.

The SPICE project, developed within the IHU Prometheus initiative, aims to build a multimodal, intelligent surveillance framework capable of identifying early physiopathological transitions in septic patients. A particular focus is placed on predicting fluid responsiveness (e.g., passive leg raising response), detecting cardiovascular mal-adaptation, and anticipating transitions between rescue, stabilization, and weaning phases.

Drawing inspiration from recent work on PLR detection through perfusion index analysis (Beurton et al., Crit Care 2019), deep temporal models for sepsis onset (Hyland et al., Nat Med 2020), and multimodal fusion for patient monitoring (Nguyen et al., IEEE TBME 2022), the project proposes to push beyond classical feature engineering and leverage modern generative and representation-learning approaches to uncover latent physiological signatures that are robust, explainable, and clinically actionable.

2. Position of the Problem

Early identification of hemodynamic deterioration relies today on threshold-based alarms and subjective interpretation of continuous data streams. These systems often fail to detect subtle precursors of circulatory collapse, suffer from alarm fatigue, and rarely adapt to individual patient trajectories.

Fluid responsiveness evaluation, although essential for avoiding fluid overload and guiding resuscitation, often requires invasive cardiac output monitoring. Non-invasive alternatives based on plethysmographic variability or perfusion index remain promising but suffer from noise, inter-patient variability, and limited generalizability across clinical contexts.

Meanwhile, AI-based methods have demonstrated impressive results in retrospective ICU datasets; however, most rely heavily on low-frequency vital signs, electronic health record data, or narrow temporal windows. High-frequency physiological waveforms, available at 100-500 Hz, remain largely underutilized despite their potential to reveal the microdynamics of perfusion and autonomic regulation.

The challenge is therefore to (i) structure and curate large-scale repositories of raw signals, (ii) extract reliable latent representations capturing patient-specific physiological states, (iii) detect clinically meaningful transitions with quantified uncertainty, and (iv) provide explainable outputs that align with the needs of bedside physicians. The postdoctoral researcher will address these challenges by combining signal processing, deep learning, Bayesian modeling, explainability tools, and ontologically guided clinical reasoning.

3. Methods and Modeling Approach
The project relies on an integrated pipeline from data acquisition to predictive modeling and clinical interpretation:

• *Multimodal High-Frequency Data Warehouse*
Compilation and synchronization of ECG, invasive/non-invasive arterial pressure, plethysmography, respiratory signals, and SpO_2 waveforms from ICU monitors (100--500 Hz). Clinical events-- fluid boluses, PLR maneuvers, vasopressor adjustments, intubation-- are time-stamped and linked to corresponding waveform segments.

• *Signal Cleaning and Canonical Event Segmentation*
Artifact detection, filtering, normalization, beat-aligned segmentation, and temporal alignment using classical and modern techniques (band-pass filtering, adaptive thresholding, dynamic time warping).

• *Learning Latent Physiological Signatures*
Development of autoencoders, variational autoencoders, sequence-to-sequence models, and Transformer architectures to obtain low-dimensional representations that capture vascular tone, autonomic response, and micro-variations in perfusion.

Bayesian networks or fuzzy-logic-based models may be incorporated to explicitly capture uncertainty and generate confidence-aware predictions.

• *Detection and Prediction Models*
Binary and multi-class classifiers for PLR response prediction, deterioration forecasting, or trajectory segmentation. Reinforcement learning-inspired models may be used for adaptive clinical decision support.

• *Explainability and Clinical Usability*
Application of XAI techniques-- temporal feature attribution, saliency maps, SHAP-based decomposition-- to ensure interpretability. Fuzzy inference systems will be explored to represent uncertain physiological thresholds in a form more aligned with clinical reasoning.

• *LLM-based Recommendation Layer*
A downstream large language model, linked to medical ontologies, will enrich the input information and translate model outputs into structured, clinically meaningful recommendations for monitoring, fluid management, or escalation.

• *Validation*
Retrospective verification on a 500-patient sepsis cohort, followed by prospective validation in collaboration with clinicians from Bicêtre hospital.

4. Supervision and Scientific Environment
The postdoctoral fellow will be hosted at Université d’Évry-- Paris-Saclay, within the IBISC laboratory (EA 4526), and co-supervised by:

Prof. Vincent Vigneron (IBISC, Université Paris-Saclay) -- expertise in signal processing, deep learning, and physiological modeling.

Prof. Xavier Monnet (Hôpital de Bicêtre, Inserm UMR_S 999) -- internationally recognized expert in hemodynamics and fluid responsiveness.

Prof. Hichem Maaref and Dr. Yasmina Sadi (Université d'Évry) -- specialists in biomedical data science and intelligent systems.

The research will be embedded in a strong, multidisciplinary ecosystem that combines computer scientists, intensivists, physiologists, and data engineers. The project benefits from the infrastructure of the IHU Prometheus program and access to hospital GPU clusters, secure data facilities (HDS-compliant), HPC resources (Jean Zay), and acquisition platforms such as Bedmaster or ixTrend.

5. Practical Information
Starting date: November 1st, 2025 (flexible).
Duration: 12 months, renewable depending on funding.
Location: Université d'Évry-- Paris-Saclay (IBISC laboratory) + partner hospital Bicêtre for clinical collaboration.
Salary: Approximately 60 k€ (including charges), according to institutional scales.

Required Profile:
PhD in AI, computer science, biomedical engineering, applied mathematics, or related fields.
Strong expertise in machine learning, deep learning, or signal processing.
Programming skills in Python, PyTorch/TensorFlow, and familiarity with HPC environments.
Experience with physiological data, ICU systems, or clinical AI is an asset.

Ability to collaborate with clinical teams and communicate results clearly.

6. What We Offer
A unique opportunity to work at the interface of artificial intelligence and critical care medicine.
Access to one of the richest multimodal waveform datasets available for sepsis research.
A highly interdisciplinary environment combining academic excellence and clinical practice.
Cutting-edge computational resources (GPU workstations, HPC clusters, secure storage).
Possibilities for international collaboration and participation in top-tier conferences (EMBC, MICCAI, IEEE TBME).
Strong support for publications, software dissemination, and potential technology transfer to industrial partners in telemonitoring and medical devices.
Integration into the IHU Prometheus innovation ecosystem.

7. Contact
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(Additional contacts for Bicêtre, Inserm UMR S 999, and Université d’Évry can be added upon request.)

8. References (selection)

[1] Beurton et al., Crit Care, 2019 -- Perfusion index for PLR detection.
[2] Mohan et al., JAMA Netw Open, 2020 -- AI for Early Sepsis Detection.
[3] Kamaleswaran et al., Crit Care Explor, 2022 -- Hemodynamic deterioration forecasting.
[4] Pimentel et al., Physiol Meas, 2019 -- ECG-based deterioration signals.
[5] Harford et al. Crit Care Med, 2021 -- Explainable Monitoring in the ICU.
[6] Hyland et al., Nat Med, 2020 -- Deep temporal models for sepsis prediction.
[7] Nguyen et al., IEEE TBME, 2022 -- Multimodal biosignal fusion.
[8] Shashikumar et al., Sci Rep, 2017 -- RNNs for ICU forecasting.
[9] Armanious et al., Physiol. Meas., 2019 -- PhysioNet Challenge on Early Sepsis Detection.
[10] Raghu et al., NeurIPS, 2017 -- RL for ICU treatment optimization.