# Personalized VR-based training using eye tracking and brain-based metrics

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## Introduction

Personalization in learning and delivery mechanisms can advance sensorimotor training outcomes across domains and user types. In this work we introduce a framework to support and evaluate personalization within virtual reality (VR) based systems.

- **Rationale:** Human sensorimotor learning has several dimensions, and VR enables an embodied training interface to promote useful behaviors.
- **Hypothesis:** Personalization driven by performance, neurophysiological, and behavioral (PNB) data can accelerate learning. This personalization can be proficiency- or deficiency-driven, with adaptation at baseline or downstream resulting in better outcomes.
- **Approach:** This work is mostly prospective, where we present evidence of using baseline PNB data for predicting performance behaviors in one VR context and discuss how that could carry forward towards a generalizable framework for adaptation.

## A framework for personalization

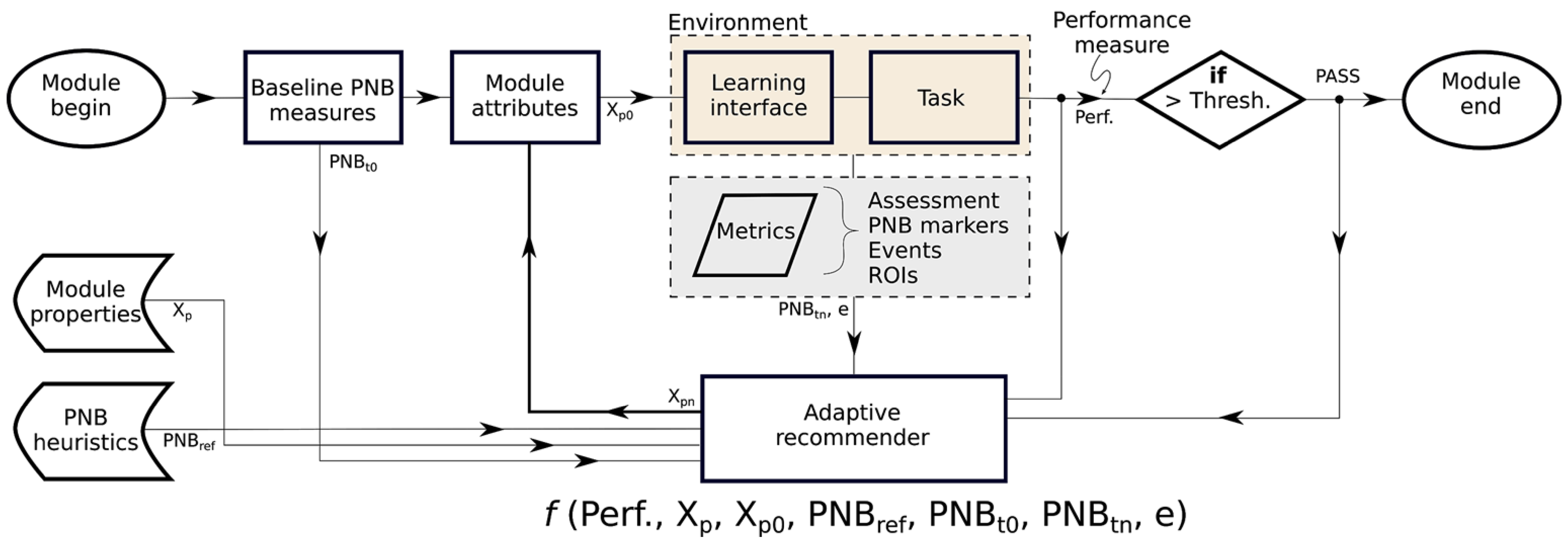



Fig. 1: Schematic representation of a technology-agnostic framework for personalization, and adaptability across learning environments and objectives.

Personalization for human learning can build on three key elements:

1. **Actionable metrics** that determine need for personalization
2. **Adaptable elements** within a learning environment or interface
3. A **guiding strategy** to facilitate personalization or adaptations

## VR training on firefighters

Forty participants were recruited from the Bryan-College Station Fire Department, who were cast into stress learning and control learning groups within a single-blind experiment protocol.

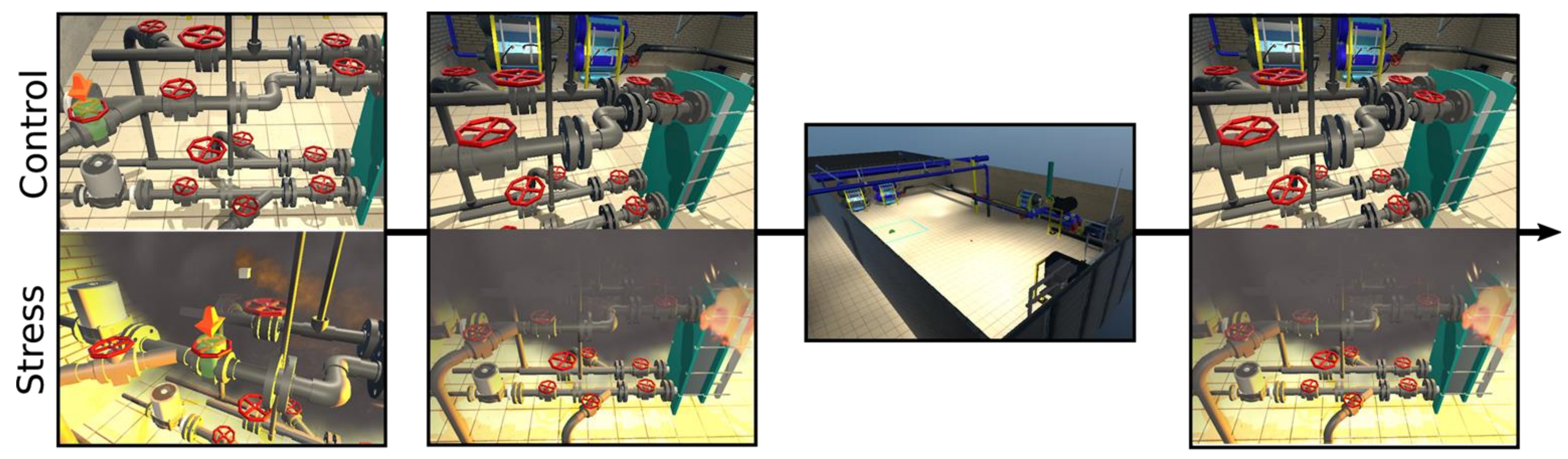
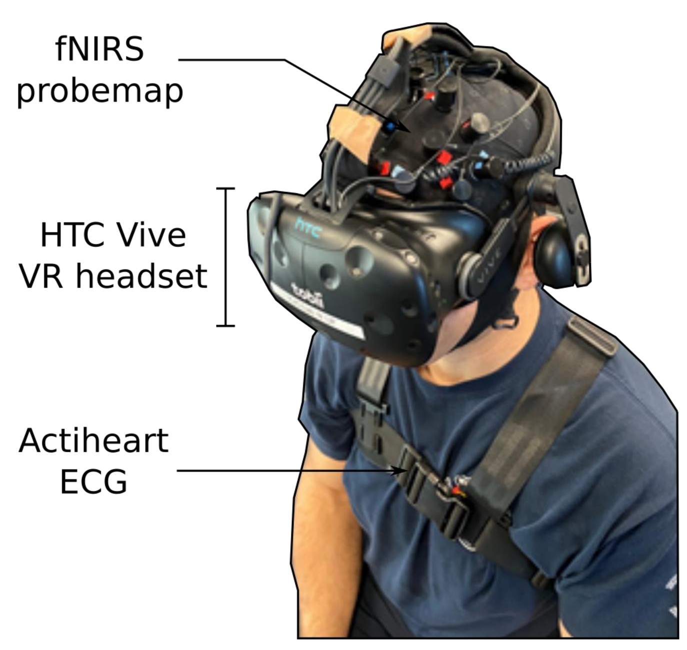



Fig. 2: (a) The experiment workflow during the VR valve sequence execution task. (b) Snapshot of an instrumented participant (RIGHT).

The task entailed distinct encoding, retention and recall phases, with audiovisual perturbations.

1. **Performance:** Correctness, time
2. **Neurophysiological:** fNIRS, ECG, EDA, eye and head movement
3. **Behavioral:** Subjective questionnaires between trials, and between levels subjective responses




## Baseline measures as performance indicators

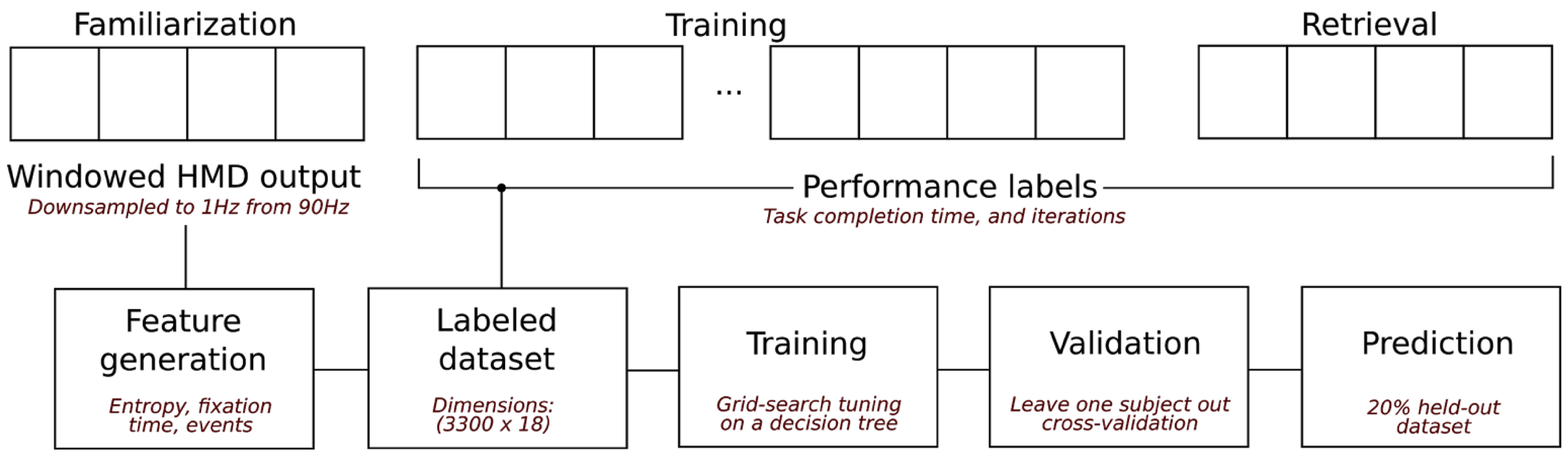



Fig. 4: The machine learning workflow used takes a supervised approach where observations are labeled based on a composite performance score that includes completion time, and response correctness.

| GROUP | ACCURACY (%) | PRECISION | RECALL |
|---|---|---|---|
| CONTROL | 86.21 | 78.24 | 71.18 |
| STRESS | 67.74 | 62.14 | 58.14 |
| OVERALL | 71.04 | 71.16 | 64.13 |

Table 1: User stratification based on baseline gaze data. All measures indicate mean values from the cross-validated output.

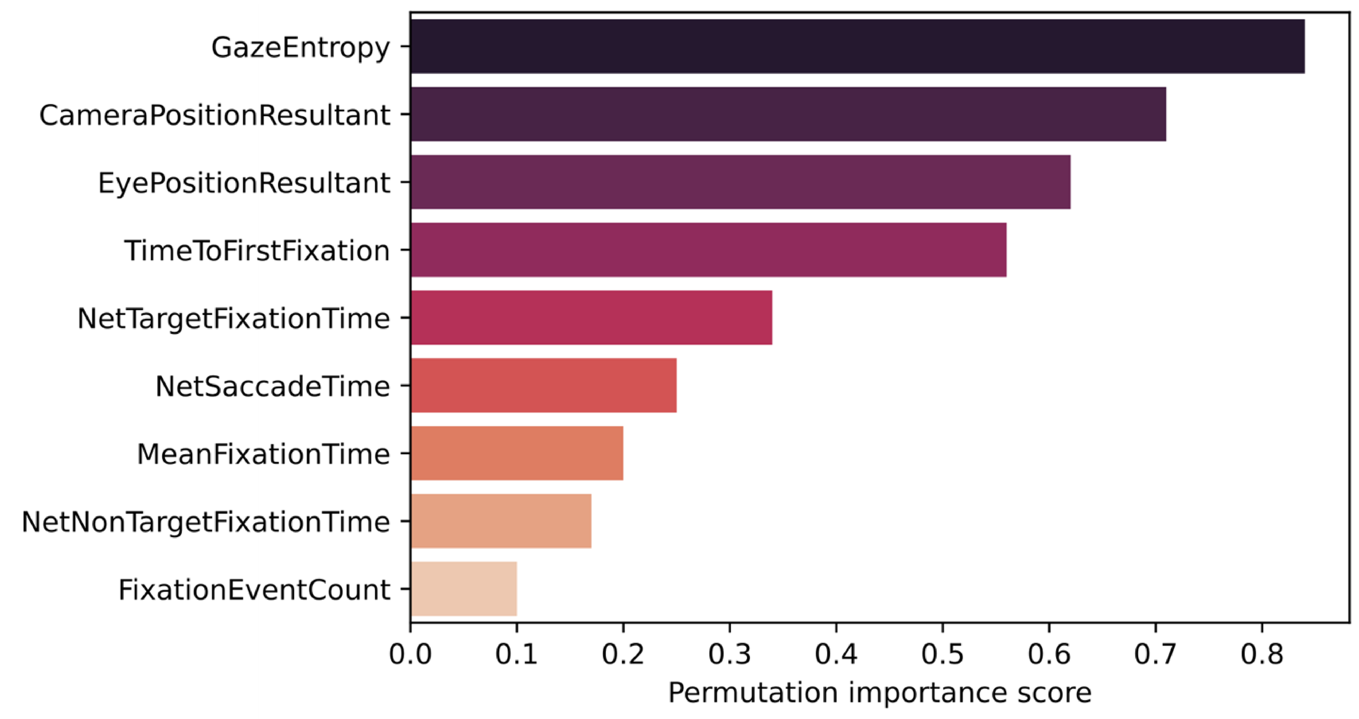
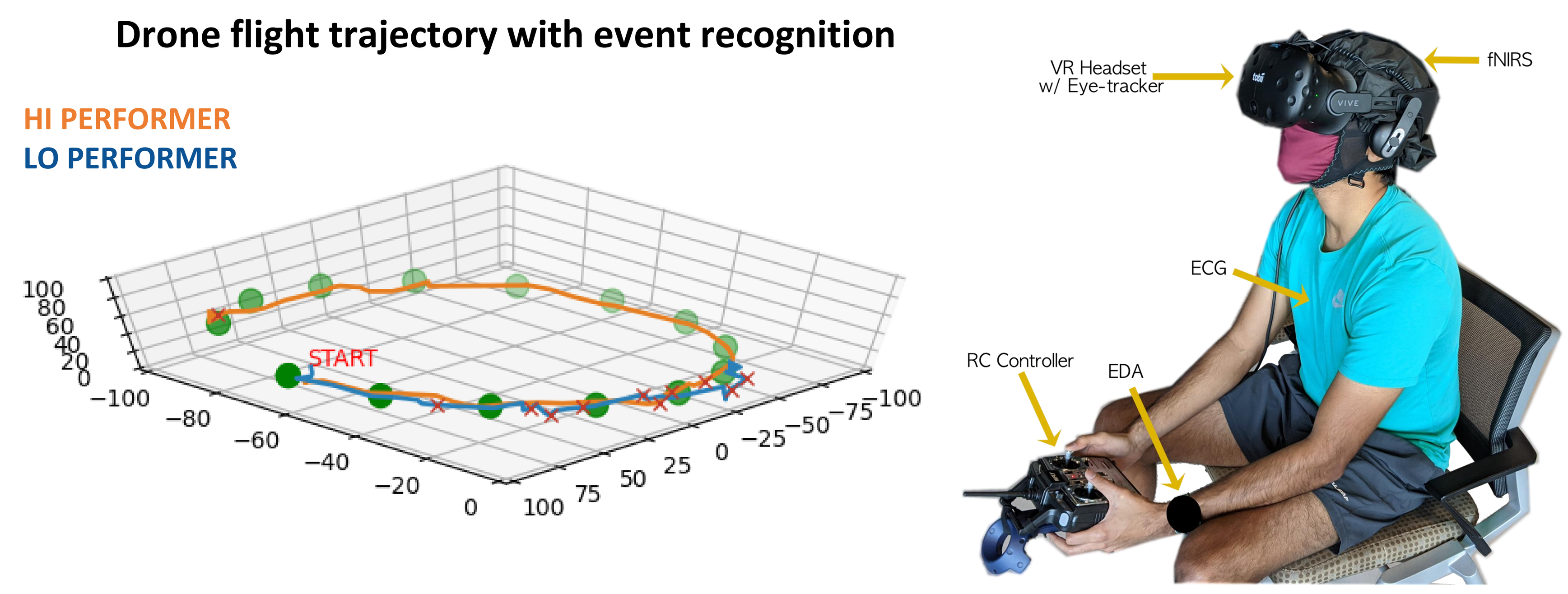



Fig. 4: Permutation importance scores for the top nine model variables used by the cross-validated model. Gaze entropy and camera position-based features were identified as key components for performance stratification.

## Towards generalizability




| | | | | |
|---|---|---|---|---|
| LO1: Familiarization | LO2: Navigation | LO3: Precision | LO4: Maneuvering | LO5: Resilience |

Fig. 5: Drone flight training in VR using a real-world RC controller. (a) Trajectory differences between high, and low performers. (b) Instrumented participant (RIGHT). (c) Training stages with learning objectives (LO).

1. This framework is now being explored across technology and task domains on an NSF convergence accelerator-driven project.
2. Brain-metrics in an offline sense can enable state-driven personalization.
3. Further explorations underway to determine the efficacy of *macro* or *micro*-adaptations.

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