Wearable Cognitive Load Monitoring for Event-Aligned Analysis in Realistic Combat Medic Training

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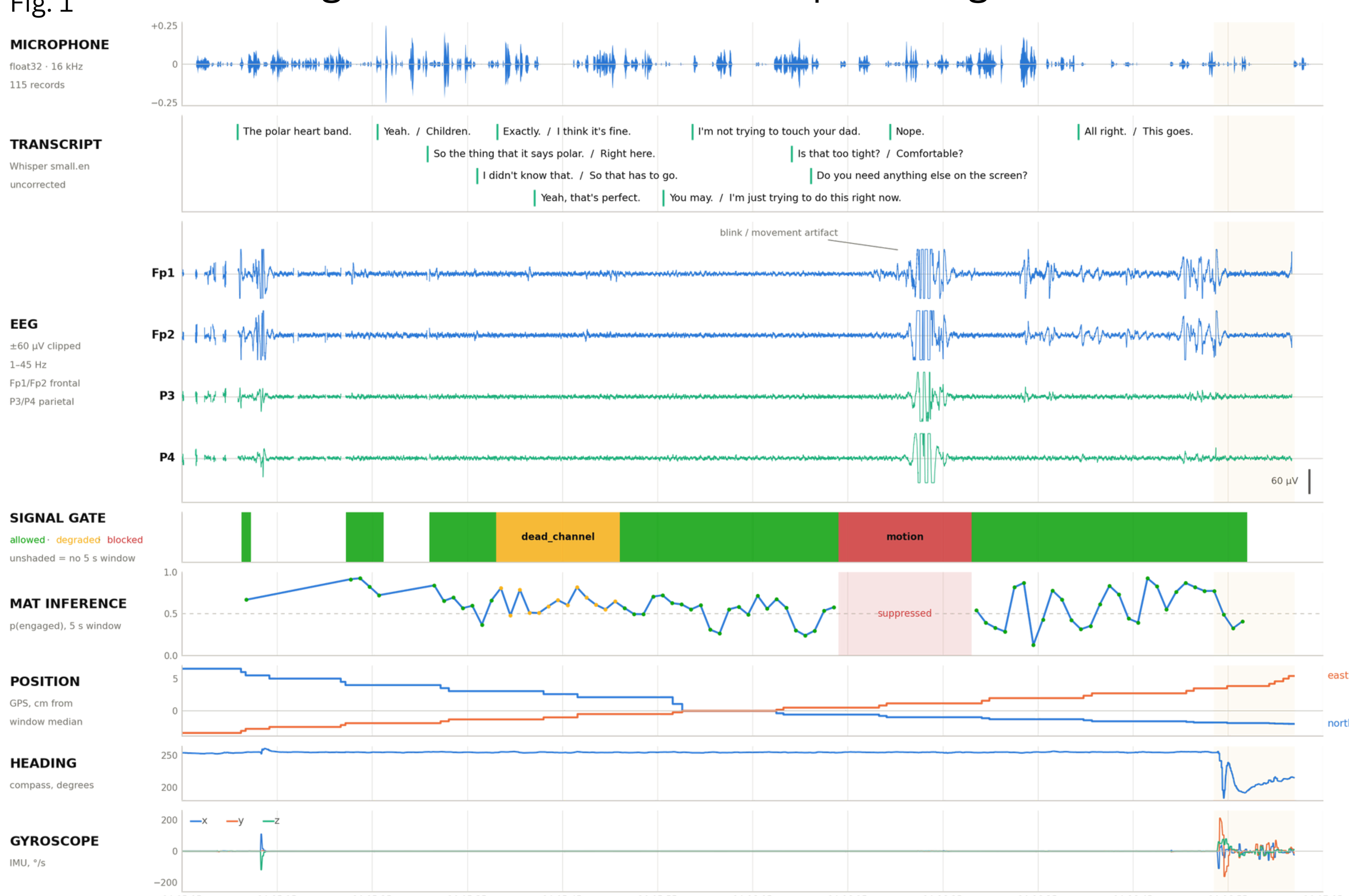
Wearable Biosensing for the Modern Medic

Modern medicine, in adverse or extreme environments, is bottlenecked by the cognitive load of the medical personel. For the future of combat medicine, human machine teams will need to be aware of internal cognitive states. The first step is being able to measure cognitive load, in real time.

Fig. 1



In partnership with USAISR (and a NASA Phase II SBIR), we built a multimodal wearable sensor package sized for the field, streamed from a body-worn Android device to a resilient, offline-capable backend. It captures the signals needed to estimate a medic's cognitive and physiological state in real time.

Wearable biosensors being used:

- Polar h10 heartrate monitor
- OpenBCI Cyton wireless EEG
- Head accelerometer
- GPS location
- Ambient sound microphones

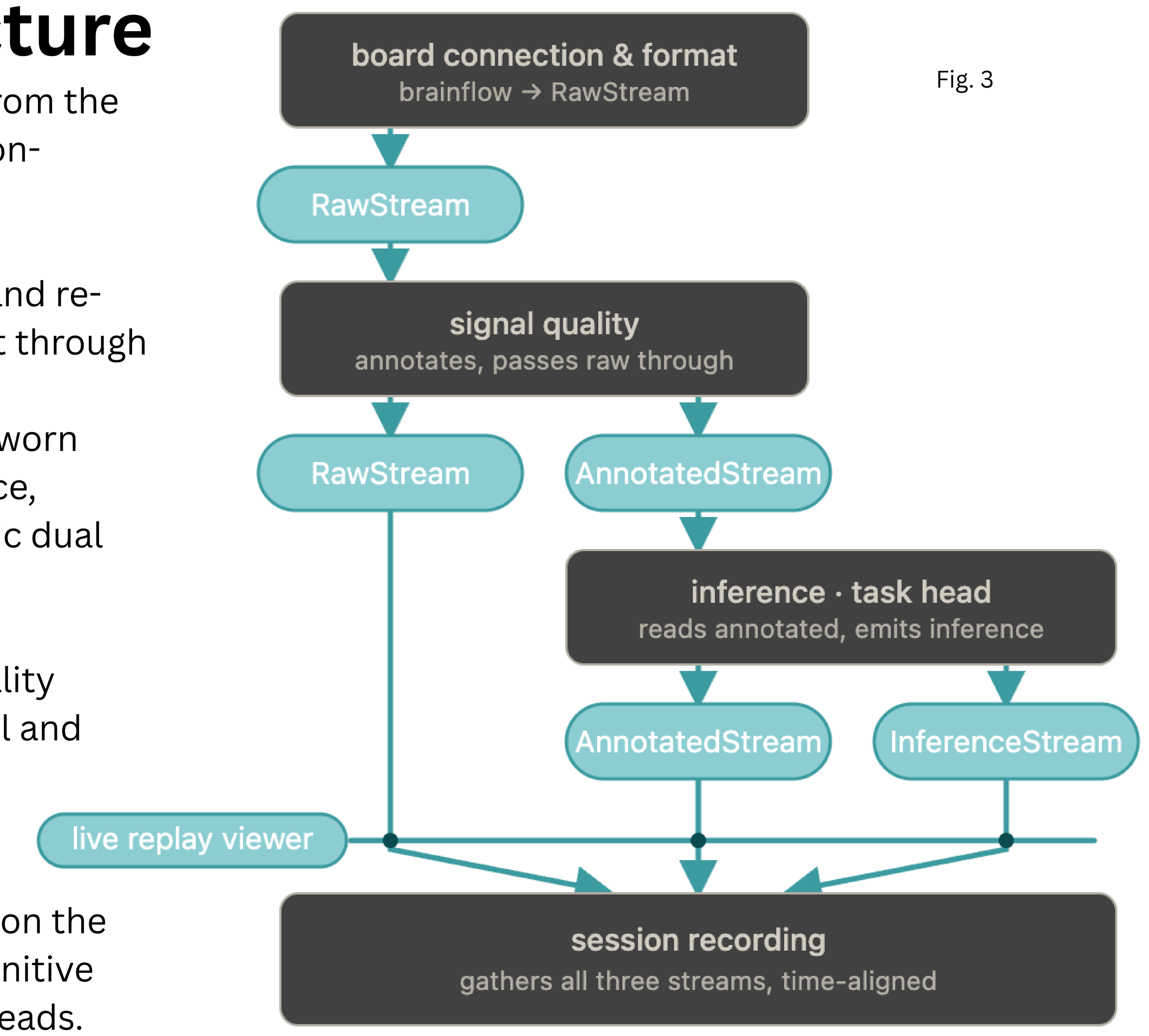
Sensor Stream Architecture

Fig. 3 shows how each biosensor datatype travels from the wearable to the dashboard under a preservative, non-destructive contract.

Every stream is recorded in full for future analysis and re-tooling. Three layers cascade, each passing its input through unchanged and adding its own:

- RawStream: Captures all data straight from the worn sensor package (EEG, cardiac, motion, impedance, packet metadata), at source rate, on a monotonic dual clock.
- AnnotatedStream: Adds time-synced signal-quality labels without altering the raw. i.e. dead-channel and motion detection, packet-loss and impedance monitoring.
- InferenceStream: captures every model verdict on the annotated stream, from deep models (REVE cognitive load) to lightweight heart-rate/eye-movement heads.

Fig. 3



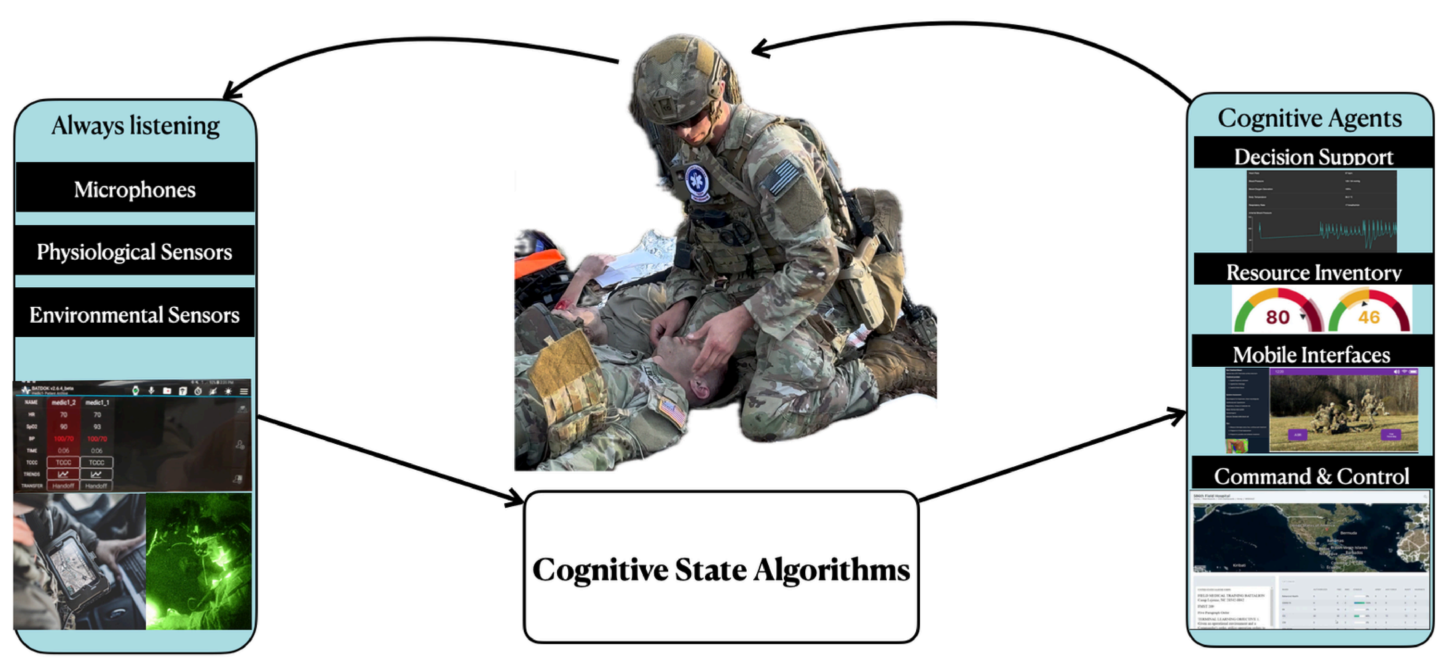
Multimodal Data, Building a Better Digital Twin.

A **psychological digital twin** is a dynamic, continuously updated virtual model of the medic's cognitive and perceptual state, built via Active Inference over multimodal biometrics. A digital twin allows hidden cognitive state analysis that would otherwise be time-counsuming, and untennable in a battlefield environment. The impacts of realtime, hidden state knowledge are a force multiplyer; for command, and proactive assistance systems for the soldier.

Cognitive load is the critical hidden state: it bottlenecks every task a medic performs, yet is invisible in any single signal (under acute stress, paramedic accuracy has been shown to fall 58%→43%[1], independent of experience). We recover it with a three-stage pipeline:

- Multimodal data: No single sensor sees cognitive load; fuse EEG + cardiac + motion + audio + location.
- Unsupervised State Discovery: With states unknown & unlabeled, discover how many latent states exist and softly assign windows.
- Hidden Markov modeling: Model the dynamics, how the medic transitions between cognitive states over time.

Fig. 2



Field Work:

On the benchtop, with our EEG equiptment and models, we achieve 0.693 balanced accuracy / 0.806 AUROC discriminating cognitively engaged from resting states during a Mental Arithmetic Task (MAT). On the NASA MATB-II operational workload battery (Neuroergonomics-2021 corpus, Z) our graded three class load head reaches 0.633 balanced accuracy / 0.793 AUROC under cross-session validation.

Here the held-out-day condition matches how the system would be deployed. Accuracy separating the easy and difficult extremes is 91%. The same head evaluated leave-one-subject-out reaches 0.644 BA / 0.856 AUROC, with all 15 subjects above three-class chance.

We are presently testing with USAISR in simulated trauma-response scenarios. We have exercised the full data pipeline end-to-end in these live scenarios: multi-sensor capture (EEG, audio, GPS, compass, IMU, cardiac), streaming ingest to the datalake, and on-line cognitive-load inference all ran in the field, producing 2,106 inference records across the 15 July collection window.

Fig. 2: Liu, Y., Zhao, J., Liu, J., Chen, Y., & Ouyang, H. (2019). Regional midterm electricity demand forecasting based on economic, weather, holiday, and events factors. IEEJ Transactions on Electrical and Electronic Engineering, 15(2), 225–234. https://doi.org/10.1002/tee.23049
[1] LeBlanc, V. R., MacDonald, R. D., McArthur, B., King, K., & Lepine, T. (2005). Paramedic Performance in Calculating Drug Dosages Following Stressful Scenarios in a Human Patient Simulator. Prehospital Emergency Care, 9(4), 439–444. https://doi.org/10.1080/10903120500255255
Zyma, I., Tukaev, S., & Seleznov, I. (2018). EEG During Mental Arithmetic Tasks. Open MIND. https://doi.org/10.13026/c2jq1p
Yassine El, O., Lys, J., Philipp, T., Farrugia, N., Bastien, P., Gripon, V., Karim, J., & Lioi, G. (2025). REVE: A Foundation Model for EEG -- Adapting to Any Setup with Large-Scale Pretraining on 25,000 Subjects. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2510.21585
Hinss, M. F., Jahanpour, E. S., Somon, B., Pluchon, L., Dehais, F., & Roy, R. N. (2022). COG-BCI database: A multi-session and multi-task EEG cognitive dataset for passive brain-computer interfaces. Zenodo (CERN European Organization for Nuclear Research). https://doi.org/10.5281/zenodo.6874128
Hinss, M. F., Darmet, L., Somon, B., Jahanpour, E., Fabien, L., Ladouce, S., & Roy, R. N. (2021). An EEG dataset for cross-session mental workload estimation: Passive BCI competition of the Neuroergonomics Conference 2021. Zenodo (CERN European Organization for Nuclear Research). https://doi.org/10.5281/zenodo.4917217