

A wearable multi-task prefrontal functional near-infrared spectroscopy methodology for studying mild traumatic brain injury: a human-subject pilot implementation

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Abstract

Background

Functional near-infrared spectroscopy (fNIRS) offers portable measurement of task-related cortical hemodynamics, but human-subject implementation requires coordinated hardware, cognitive stimulation, signal processing, and analysis. We describe an integrated wearable multi-task prefrontal fNIRS methodology implemented in a mild traumatic brain injury (mTBI) pilot cohort.

Methods

The methodology combined a continuous-wave dual-wavelength system (730/850 nm; four channels; approximately F7, Fp1, Fp2, and F8; 17 Hz), a programmed four-task battery comprising verbal fluency, concentration with neurofeedback, mental arithmetic, and spatial sequence search, and a common processing sequence using TDDR, the modified Beer-Lambert law, 0.1-Hz low-pass filtering, resting-baseline correction, normalization, and vector-based hemodynamic indices.

Results

All 40 participants represented in the retained analytical record had documentation of the programmed acquisition and four-task procedure. Screening and early-discontinuation logs were unavailable; therefore, an enrollment-based completion rate could not be estimated. The programmed task blocks totalled 1030 s (approximately 17.2 min), excluding setup and task transitions. The groups differed in age and sex distribution. A post hoc sex-only descriptive rule correctly classified 28/40 participants (70%; exact 95% CI, 53.5%-83.4%), illustrating substantial demographic confounding. Retained pooled out-of-fold fNIRS classifications were correct for 27/36 participants (75%; exact 95% CI, 57.8%-87.9%), but the original feature and model selection was not fully nested and incremental value beyond demographics was not established.

Conclusions

The principal contribution is documentation of a human-subject implementation integrating compact bilateral prefrontal acquisition, four complementary cognitive challenges, and a common stage-aware hemodynamic representation workflow. Complete procedure records in the analysed cohort do not establish an enrollment-based completion rate, tolerability, signal yield, artifact reduction, diagnostic accuracy, incremental fNIRS value beyond demographics, or generalizability.

Background

Mild traumatic brain injury (mTBI) is among the most common forms of traumatic brain injury and may be associated with persistent deficits in attention, working memory, executive function, and information-processing speed [1]. Although computed tomography and magnetic resonance imaging are essential for detecting structural lesions and ruling out acute complications, conventional imaging may fail to capture subtle functional abnormalities in patients whose symptoms persist after an apparently mild injury [2]. This gap has motivated the development of complementary physiological measures that can characterize functional brain responses during cognitively demanding tasks.

Functional near-infrared spectroscopy (fNIRS) measures changes in oxygenated and deoxygenated hemoglobin associated with cortical activity. Compared with conventional neuroimaging modalities, fNIRS is portable, relatively low cost, tolerant of naturalistic task settings, and suitable for repeated monitoring [3, 4]. Prior studies have used fNIRS to evaluate brain responses after traumatic brain injury and have suggested that altered prefrontal hemodynamics may accompany cognitive impairment in this population [1, 5, 6]. Best-practice recommendations for fNIRS publications further emphasize transparent reporting of optode placement, preprocessing, and analysis decisions [7].

The methodological contribution of this study comprises three integrated components: (1) compact bilateral prefrontal acquisition using a wearable dual-wavelength four-channel system; (2) a single-session cognitive battery sampling verbal fluency, sustained attention with neurofeedback, arithmetic working memory, and spatial executive processing; and (3) a common stage-aware workflow covering optical-density conversion, motion correction, hemoglobin-concentration estimation, filtering, baseline correction, normalization, and derived hemodynamic representation. The primary objective was to document human-subject implementation of the complete methodology in the retained 40-participant pilot cohort. Aggregate classification is retained only as a secondary downstream illustration and not as diagnostic-model validation. Consistent with guidance for non-randomized pilot and feasibility studies, implementation evidence is distinguished from later confirmatory evaluation [8].

Results

Human-subject implementation

All 40 participants represented in the retained analytical record had documentation of the programmed acquisition and four-task procedure. Because screening, exclusion, and early-discontinuation logs were unavailable, an enrollment-based protocol-completion rate could not be estimated. No retained aggregate measures were available for setup time, participant tolerability, adverse events, channel yield, missingness, or artifact burden; therefore, these records must not be interpreted as evidence of high tolerability, operational stability, or improved signal quality.

Participant characteristics

The healthy control group included 13 males and 7 females, whereas the mTBI group included 5 males and 15 females. The mean age was 46.25 +/- 15.61 years in the control group and 59.05 +/- 17.70 years in the mTBI group. The mean age difference was 12.8 years (approximate 95% CI, 2.1–23.5 years; Hedges' g = 0.75). Group differences were observed in age (p = 0.020) and sex distribution (p = 0.025). As a post hoc descriptive demographic benchmark, a rule classifying female participants as mTBI and male participants as controls correctly classified 28/40 participants (apparent accuracy, 70%; exact 95% CI, 53.5%-83.4%; sensitivity, 75%; specificity, 65%). The rule was derived and evaluated in the same full cohort and is not a cross-validated prediction model. Participant characteristics are summarized in Table 2, and the age-frequency distributions of both groups are shown in Fig. 2.

Table 2 Participant characteristics			
Characteristic	Control	mTBI	p-value
Participants	20	20	Not applicable
Sex (male/female)	13/7	5/15	0.025
Age (years)	46.25 +/- 15.61	59.05 +/- 17.70	0.020

Age was compared using Welch's independent t-test; sex distribution was compared using Fisher's exact test.

Exploratory feature screening

For the combined VFT, CT, MAT, and SSST feature set, the original uncorrected screen retained 169 candidate features. The dimensionality-reduction visualization was removed because it followed supervised, uncorrected feature screening and could create a circular impression of group separation. The eight representative p-values preserved in the original report ranged from 0.0005 to 0.0461; none met the conservative Bonferroni threshold for 864 comparisons ($\alpha = 0.05/864 = 5.79 \times 10^{-5}$). These retained feature-level observations are therefore not interpreted as statistically confirmed group differences or biomarkers.

Classification performance

The retained original analysis evaluated several tasks, task combinations, and model classes. For the four-task MLP, apparent training accuracy was 93%, pooled out-of-fold accuracy was 27/36 (75%; exact 95% CI, 57.8%-87.9%), and the four-participant holdout result was 3/4 (75%; exact 95% CI, 19.4%-99.4%). These values do not establish model superiority or incremental value beyond demographics because feature and model selection was not fully nested. Detailed retained aggregate tables and fold-level confusion matrices are provided in Additional file 1; ROC curves were removed because participant-level scores were unavailable.

The three internal-validation folds each contained 12 participants and produced 9/12 correct classifications (75%; exact 95% CI, 42.8%-94.5%). Pooled out-of-fold classifications were correct for 27/36 participants (75%; exact 95% CI, 57.8%-87.9%). These intervals quantify binomial sampling uncertainty only and do not correct selection-related optimism. Fold-specific AUC values and descriptive confusion matrices are retained in Additional file 1.

Discussion

The principal contribution of this pilot report is the documented human-subject implementation of an end-to-end wearable multi-task prefrontal fNIRS methodology. Its reusable methodological core links compact bilateral acquisition, four complementary cognitive challenges, stage-aware processing, and an orthonormal 45-degree transformation of the ΔHbO_2 - ΔHHb plane into ΔCBV and ΔCOE , with $|\text{L}|$ preserving vector magnitude. These reconstructable components can be implemented independently of the legacy Angle K calculation and the unavailable classifier pipeline. The aggregate classification analysis remains only a secondary downstream illustration and does not establish diagnostic performance because demographic confounding, high-dimensional non-nested feature selection, and substantial sampling uncertainty remain unresolved.

The engineering rationale for combining tasks is that each task imposes a different prefrontal cognitive demand. VFT emphasizes overt verbal generation and executive retrieval; CT probes sustained attention with hemodynamic neurofeedback; MAT stresses arithmetic working memory; and SSST targets sequential spatial search and executive control. The programmed blocks totalled approximately 17.2 min, offering task diversity within a compact session. This integration, rather than classifier accuracy, is the central methodological contribution. The dimensionality-reduction figure was removed because it was not independent of the preceding uncorrected feature screen.

Methodological transparency is strengthened by the retained component specifications, programmed task timing, processing sequence, and reconstructable equations for ΔCBV , ΔCOE , and $|\text{L}|$. Angle K is retained only as a legacy analytical feature because its reference-axis and quadrant implementation could not be reconstructed. These records do not substitute for the unavailable participant-level analytical dataset, exact software environment, channel-quality decisions, or complete column-level feature dictionary.

Interpretive boundaries of the retained hemodynamic results

The retained aggregate documentation confirms completion of the acquisition and feature-processing workflow but does not support claims of impaired oxygen extraction, altered vascular recruitment, inefficient neurovascular coupling, or delayed physiological recovery.

Accordingly, the defensible contribution is the documented human-subject implementation of the wearable acquisition system, task battery, and stage-aware representation workflow, rather than confirmation of an mTBI-specific hemodynamic mechanism. The retained hardware and protocol records improve methodological transparency, but the missing executable pipeline and unreconciled 864-column feature dictionary prevent a claim of complete computational reproducibility.

The performance level observed here should be interpreted cautiously. The training accuracy was higher than the validation and testing accuracies, which may indicate overfitting in the setting of high-dimensional features and a small sample. Moreover, the control and mTBI groups differed significantly in both age and sex distribution. Because fNIRS hemodynamic responses can be affected by demographic and physiological factors, some of the observed classification performance may reflect confounding rather than mTBI-related neurophysiological differences alone.

Because age and sex differed between groups, residual demographic confounding cannot be fully excluded. The most direct confirmatory comparison would be an age-and-sex-only model tested against a covariate-adjusted fNIRS model in which each feature is residualized for age and sex using training-fold parameters. Such analyses were not available for the present cohort. Therefore, incremental validity beyond age and sex was not demonstrated in this study.

The high-dimensional feature-selection strategy also requires caution. Screening 864 candidate features with uncorrected two-sample tests creates a substantial false-positive risk and is not sufficient for confirmatory feature claims or an unbiased estimate of predictive performance. The revised interpretation therefore avoids presenting the selected features as definitive biomarkers. Future analyses should report FDR-adjusted results and test embedded or wrapper selection methods, such as elastic net or L1-penalized logistic regression, inside nested cross-validation. This would directly address multiple comparisons while reducing overfitting pressure before nonlinear model fitting.

The study has several limitations. First, the sample size was small and recruited from available participants, limiting statistical power and external generalizability. Second, the groups were not demographically matched; therefore, residual confounding by age or sex cannot be fully excluded. Third, the original analysis did not include permutation-based significance testing; therefore, the observed accuracy has not been shown to exceed the empirical chance distribution of the complete modelling pipeline. Fourth, the exact hyperparameter search ranges, random seeds, fold assignments, and complete software environment were not preserved in the retained analysis record, preventing full computational reproduction of the machine-learning results. Fifth, the analysis was exploratory and should not be interpreted as clinical diagnostic validation. Sixth, the fNIRS system measured only four prefrontal channels, which improves portability but limits spatial coverage. Finally, model selection and feature selection require validation in independent datasets to determine whether the observed performance is reproducible.

Additional protocol-specific limitations should be noted. The retained protocol describes the task sequence as VFT, CT, MAT, and SSST, and no counterbalancing or randomization record was retained;

therefore, task-specific responses may include order, fatigue, practice, or carry-over effects. The CT used closed-loop fNIRS neurofeedback, so CT-derived hemodynamic features should not be interpreted as responses to an entirely independent externally controlled cognitive challenge. Complete behavioral performance measures were not retained, preventing verification of equivalent task engagement or difficulty across groups. Injury chronicity, time since injury, injury mechanism, and symptom severity were also unavailable in the retained analytical record and could not be incorporated into interpretation.

Future studies should prospectively recruit larger age- and sex-matched cohorts, prespecify low-dimensional physiological endpoints, incorporate demographic covariates and demographic-only baselines, repeat all preprocessing and feature selection within leakage-safe nested validation, conduct pipeline-level permutation testing, and validate any predictive model in an independent external dataset. Expanded channel coverage and standardized task-performance measures should also be considered.

Conclusions

This study documents a human-implemented methodology integrating a wearable four-channel prefrontal fNIRS system, four complementary cognitive challenges, and a common stage-aware hemodynamic representation workflow. Implementation of the programmed procedure was documented in the retained 40-participant analytical cohort. However, the absence of screening, exclusion, and early-discontinuation logs prevents estimation of an enrollment-based completion rate or procedural feasibility. The retained classification results remain illustrative aggregate observations subject to demographic confounding, non-nested high-dimensional feature selection, and wide uncertainty. Confirmatory claims require a new prospectively matched and fully reproducible study.

Methods

Study design and participants

The retained study record describes a single-center observational pilot cohort enrolled under approved protocols. The machine-learning evaluation reported here was an exploratory analysis of the available analytical cohort, which comprised 40 participants: 20 healthy controls and 20 patients with mTBI. Participants in the mTBI group were diagnosed by neurologists at Taipei Veterans General Hospital according to clinical criteria. Recruitment was not prospectively matched for age or sex. Consequently, the study design cannot separate diagnosis-related effects from demographic effects, and demographic confounding is treated as a major limitation rather than as a problem resolved by statistical adjustment.

No prespecified or cross-validated demographic-only prediction model and no age- or sex-adjusted group comparison were available in the original analysis. We therefore added only a post hoc aggregate sex-only descriptive benchmark. The reported fNIRS associations and classification results remain unadjusted and are not evidence of diagnostic information independent of age and sex.

Eligible participants were at least 20 years old. Healthy controls had no history of neurological or major systemic disease. The mTBI inclusion criteria included a Glasgow Coma Scale score of 13–15, no significant intracranial injury on CT or MRI, loss of consciousness shorter than 1 hour when present, and altered mental state such as drowsiness, confusion, or delayed response. Exclusion criteria included inability to understand task instructions or complete cognitive testing and fNIRS measurement, wounds, edema, or other abnormalities over the frontal measurement area that could interfere with optical transmission, prior neurological disease, and history of alcohol or drug abuse.

Age differences between groups were assessed using Welch's independent t-test, and sex distribution was compared using Fisher's exact test. No a priori power calculation was performed because this was an exploratory pilot study.

Post hoc descriptive calculations used only retained aggregate counts and summary statistics. Exact Clopper-Pearson confidence intervals were calculated for the 28/40 sex-only rule, the 27/36 pooled out-of-fold classifications, and the 3/4 holdout classifications. The sex-only rule classified female participants as mTBI and male participants as controls; because the rule was derived and evaluated in the same full cohort, it is an apparent descriptive benchmark rather than a validated prediction model. The age mean difference, an approximate Welch confidence interval, and Hedges' g were calculated from the retained group means, standard deviations, and sample sizes.

Wearable fNIRS system

Prefrontal hemodynamics were recorded using an in-house continuous-wave wearable fNIRS system. The retained engineering documentation identifies a Marubeni America L4*730/4*805/4*850-40Q96 LED module operated at 730 and 850 nm, with a reported average optical output of approximately 2–4 mW, and Texas Instruments OPT101 monolithic photodetectors. Sources and detectors were arranged at a fixed 30-mm separation to form four prefrontal channels positioned approximately at F7, Fp1, Fp2, and F8 according to the international 10–20 system. Signals were sampled at 17 Hz. An ESP32 microcontroller coordinated acquisition and transmitted data by Bluetooth to a laptop interface that supported source-intensity adjustment, real-time signal display, task control, and CSV storage of signals with task timing.

Cognitive task protocol

The optodes were integrated into a padded headform modified from a commercial virtual-reality headset with an adjustable rear dial and elastic straps. This structure was designed to facilitate repeatable prefrontal positioning, maintain optode-scalp contact, and limit small head movements; no retained comparative data were available to quantify improvement in coupling or motion artifacts. Testing was conducted in an independent clinical room. Participants were seated, fitted with the headset, and instructed to minimize head movement. The retained protocol documents the task sequence as VFT, CT, MAT, and SSST. Programmed task blocks totalled 1030 s (approximately 17.2 min), excluding equipment setup and transitions. The four cognitive tasks and their programmed timing are summarized in Table 1.

Table 1
Cognitive tasks and timing

Task	Primary cognitive domain	Task structure
VFT	Language fluency and executive retrieval	30-s eyes-closed rest; 60-s overt word generation in three 20-s phonetic-cue periods; 70-s eyes-closed recovery.
CT	Sustained attention and hemodynamic neurofeedback	Five rounds: 5-s eyes-open rest; 30-s airplane task with height mapped to frontal ΔHbO_2 (rise threshold 0.25 μM above rest mean); 5-s visual reinforcement; 20-s eyes-closed recovery.
MAT	Arithmetic working memory	30-s eyes-closed rest; 180-s three-digit $\pm$ two-digit multiple-choice arithmetic with immediate feedback; 60-s eyes-closed recovery.
SSST	Spatial working memory and executive control	Six rounds: 5-s fixation; 30-s sequential spatial search with 4, 6, then 8 numbered targets; 15-s eyes-closed recovery.

Stage-aware signal processing and physiological representation

Raw optical intensity was converted to optical density and motion-corrected using temporal derivative distribution repair (TDDR) [10]. Changes in oxygenated hemoglobin (ΔHbO_2) and deoxygenated hemoglobin (ΔHHb) were calculated using the modified Beer-Lambert law with a 30-mm source-detector distance and differential pathlength factors of 6.0172 at 730 nm and 4.9399 at 850 nm. The retained workflow then applied a fourth-order Butterworth low-pass filter at 0.1 Hz using forward-backward zero-phase filtering, followed by subtraction of the mean of the corresponding pre-task resting interval.

The retained linear-transform indices in the ΔHbO_2 - ΔHHb plane were defined as follows [11, 12]:

$$\Delta\text{CBV} = (\Delta\text{HHb} + \Delta\text{HbO}_2)/\sqrt{2}$$

$$\Delta\text{COE} = (\Delta\text{HHb} - \Delta\text{HbO}_2)/\sqrt{2}$$

$$|L| = \sqrt{(\Delta\text{COE})^2 + (\Delta\text{CBV})^2}$$

The retained thesis records the ratio expression $\text{Angle } K = \arctan(\Delta\text{COE}/\Delta\text{CBV})$. However, the cited vector-analysis method defines an included angle relative to the positive ΔO axis and distinguishes phase by quadrant [11]. The original reference-axis conversion, quadrant handling, and behavior at $\Delta\text{CBV} = 0$ were not preserved. Angle K is therefore reported only as a legacy feature of the original analysis and is not presented as a reproducible component of the revised methodology. Min-max normalization was defined using the minimum and maximum of the analysed time series, but the exact participant/channel/task grouping used to determine those extrema was not preserved.

Signals were segmented into rest, task, reinforcement when applicable, and recovery stages. The retained documentation defines stage-based descriptive and temporal features from ΔHbO_2 , ΔHHb , ΔCBV , ΔCOE , $|L|$, and the legacy Angle K feature, including mean, standard deviation, skewness, kurtosis, slope or trend, and stage area under the curve. The original manuscript reports 864 candidate features.

Because the Angle K phase implementation and a one-to-one map of all 864 columns could not be reconstructed, neither is presented as a reproducible component of the revised methodology. The complete methodological workflow is illustrated in Fig. 1.

Secondary exploratory classification workflow

The classification analysis was designed as an exploratory machine-learning evaluation rather than a clinically deployable diagnostic model. In the original analysis, candidate features were screened using independent two-sample t-tests with an uncorrected threshold of $p < 0.05$. The available cohort was first divided in a 90:10 ratio into a 36-participant development set and a four-participant holdout set; three-fold cross-validation was then performed within the development set. All observations from a participant were kept in the same partition. The original workflow did not implement fully nested feature selection, in which screening is repeated independently inside every inner training fold. This limitation can introduce optimistic bias and is explicitly acknowledged [9].

Because 864 candidate features were screened, the uncorrected $p < 0.05$ procedure was vulnerable to multiple-testing false positives. No selected feature was shown to survive family-wise-error or false-discovery-rate correction; accordingly, the feature-level findings are described as exploratory effect patterns rather than statistically confirmed biomarkers. A confirmatory analysis would require prespecified feature families or false-discovery-rate control, with scaling, covariate handling, feature selection, and tuning repeated entirely within nested training loops.

The evaluated models included linear discriminant analysis, quadratic discriminant analysis, logistic regression, support vector machine, k-nearest neighbors, multilayer perceptron (MLP), and XGBoost. Model performance was assessed using accuracy, precision, recall, F1-score, confusion matrices, receiver-operating characteristic curves, and AUC. Within the 36-participant development set, participant-level, stratified three-fold cross-validation was used. Each validation fold contained 12 participants (6 healthy controls and 6 participants with mTBI). The remaining four participants constituted the holdout set. Given its size, the holdout result is descriptive and is not treated as an independent validation capable of establishing generalizability. The four-participant holdout set was not intended for model fitting. However, the exact hyperparameter search ranges, random seeds, fold assignments, and complete software environment were not preserved in the available analysis record. This limits computational reproducibility, and the manuscript reports only details that could be verified from retained documentation. The retained aggregate results for the evaluated tasks and model classes are provided in Additional file 1 for transparency; they are not used to claim model superiority.

An AI-assisted writing tool was used during manuscript preparation to support language editing, formatting, and journal-structure alignment. The tool was not used for study design, data collection, statistical analysis, or generation of the reported results. All scientific content was reviewed by the authors, who remain responsible for the final manuscript.

Abbreviations

- AMS
alteration of mental state
- AUC
area under the receiver-operating characteristic curve
- CBV
cerebral blood volume
- COE
cerebral oxygen exchange
- CT
concentration task
- DPF
differential pathlength factor
- FDR
false-discovery rate
- fNIRS
functional near-infrared spectroscopy
- GCS
Glasgow Coma Scale
- HHb
deoxygenated hemoglobin
- HbO₂
oxygenated hemoglobin
- IRB
institutional review board
- LOC
loss of consciousness
- MAT
mental arithmetic task
- MBLL
modified Beer-Lambert law
- MLP
multilayer perceptron
- mTBI
mild traumatic brain injury
- PFC
prefrontal cortex
- ROC
receiver-operating characteristic

- SSST
spatial sequence search task
- TDDR
temporal derivative distribution repair
- VFT
verbal fluency task
- XGB
extreme gradient boosting

Declarations

Ethics approval and consent to participate

Recruitment of healthy controls was approved by the Institutional Review Board of National Yang Ming Chiao Tung University (IRB No. NYCU-REC-110-014F), and recruitment of participants with mTBI was approved by the Institutional Review Board of Taipei Veterans General Hospital (IRB No. 2024-08-002CC). Written informed consent was obtained from all participants before enrollment. All procedures involving human participants were conducted in accordance with the Declaration of Helsinki and its later amendments.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Authors' information

Not applicable.

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Author Contribution

C.W.S. conceived and supervised the study. C.Y.W. contributed to experiment implementation, data processing, machine-learning analysis, and initial manuscript preparation. Y.H.H. and S.P.C.H. contributed to clinical recruitment and clinical interpretation. C.C.S. contributed to fNIRS system development and technical analysis. All authors contributed to manuscript revision and read and approved the final manuscript.

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Not applicable.

Data Availability

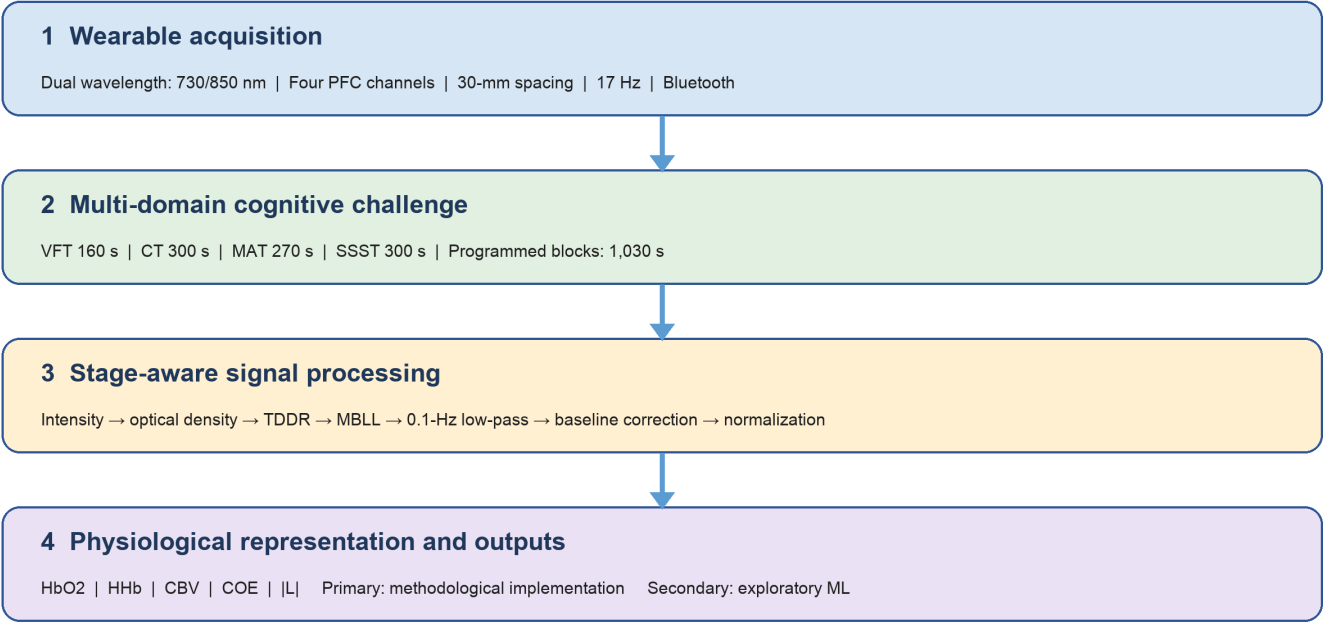
The participant-level analytical dataset and executable analysis pipeline were not available to the revising authors and therefore cannot be shared or reanalysed. The retained aggregate results and methodological documentation are provided in Additional file 1. No participant-level results were reconstructed from aggregate summaries.

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Figures



Angle K from the original analysis is not shown because its phase implementation could not be reconstructed.

Figure 1

End-to-end methodological architecture. The primary contribution integrates wearable acquisition, a four-task cognitive challenge, stage-aware signal processing, and physiological representation. Aggregate machine-learning results are retained only as a secondary exploratory application.

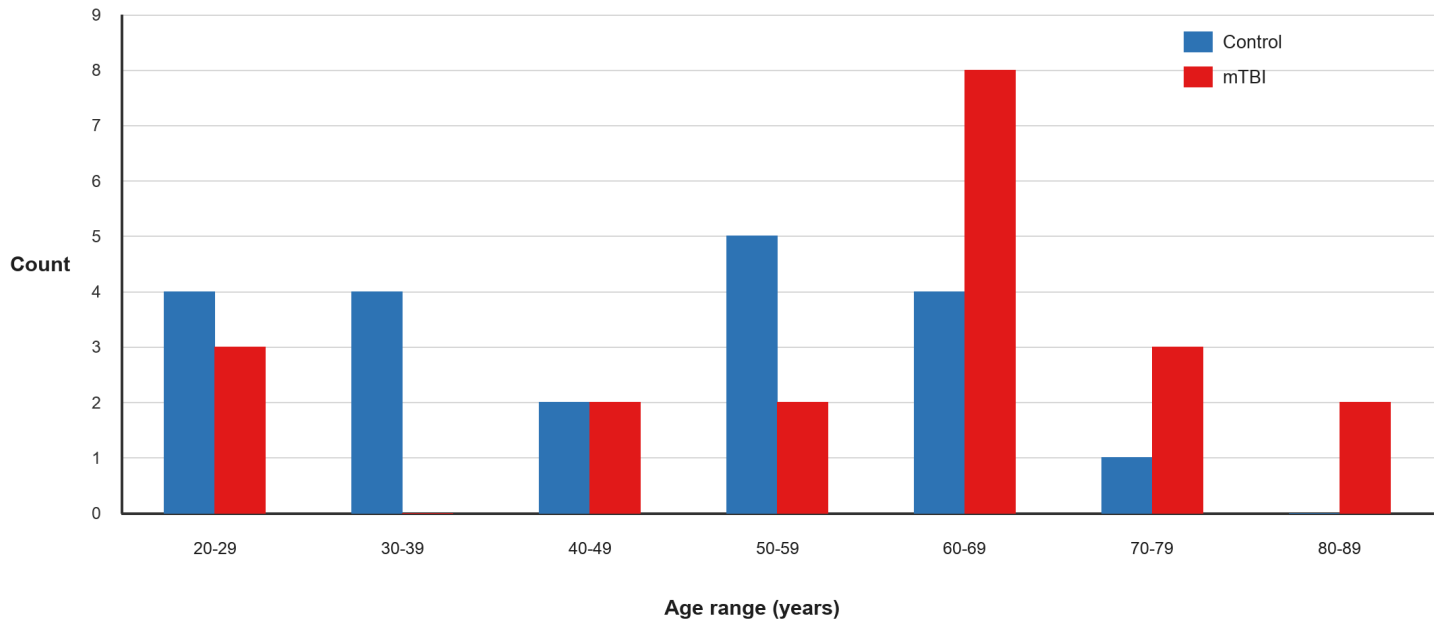


Figure 2

Age-frequency distributions across predefined age intervals for 20 controls and 20 participants with mTBI. Age-bin counts were transcribed from the retained original aggregate age-frequency figure; participant-level ages were unavailable for reanalysis. Mean age was 46.25 +/- 15.61 years in controls and 59.05 +/- 17.70 years in the mTBI group; the mean difference was 12.8 years (approximate 95% CI, 2.1-23.5; Welch's t-test p=0.020).

Supplementary Files

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