Physiological Deconditioning Markers as Predictors of Cognitive Performance Decline: A Feasibility Study in Spaceflight-Analogue Bed Rest

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Synopsis

This feasibility study evaluates whether peripheral physiological markers can predict cognitive performance changes during spaceflight-analogue bed rest. Using NASA Life Sciences Data Archive head-down tilt bed rest data from 23 participants (n = 223 analysable sessions), three machine learning regression models were benchmarked using chronological splitting and subject-wise lag feature engineering. Support Vector Regression achieved the highest single-split R^2 (0.79, MAE = 29.33 ms); Random Forest demonstrated the most stable cross-validated performance (CV R^2 = 0.68, SD = 0.04). Prior cognitive state and monosynaptic reflex latency emerged as primary predictors, supporting the feasibility of physiological-marker-based cognitive monitoring.

Background

Astronauts on long-duration missions are exposed to a constellation of physiological stressors, including microgravity, fluid shifts, and musculoskeletal deconditioning, that collectively place the central nervous system under sustained challenge [1, 2]. Structural and fluid-dynamic changes in the brain have been documented following extended spaceflight, raising legitimate questions about the integrity of cognitive function over mission timescales [3, 4]. Despite this, cognitive monitoring in operational spaceflight continues to rely on periodic, scheduled assessments. Validated batteries such as the Cognition test battery have advanced the field considerably [5], yet discrete time-point measurement cannot capture the dynamic, day-to-day fluctuations in cognitive state that may be most operationally consequential.

A more informative approach would be to identify physiological signals that track cognitive performance continuously and passively, without placing additional burden on the crew. In the present study, it was investigated whether physiological markers routinely collected during head-down tilt bed rest, including monosynaptic reflex latency and cardiac output indices, carry predictive information about psychomotor processing speed and support low-burden cognitive monitoring for long-duration space exploration missions.

Methods

Dataset and Participants
Publicly available head-down tilt bed rest data were obtained from the NASA Life Sciences Data Archive. The dataset included longitudinal physiological and cognitive measurements from 23 participants across multiple bed rest sessions, resulting in 266 valid administrations of the Computerised Portable Test battery (WinSCAT). Computerised Portable Test Reaction Time (CPTRT), a continuous measure of psychomotor processing speed, was selected as the outcome variable.

Feature Engineering and Preprocessing
To maintain temporal order and avoid data leakage, subject-specific lag features (t−1) were

generated using each participant's previous cognitive assessment. This ensured that only historical within-subject information informed model training. Current CPTA and CPTL values were excluded from the predictors. After removing initial observations lacking lag values, the final dataset contained 223 observations from 23 participants. Categorical variables were one-hot encoded for Support Vector Regression and Random Forest, while XGBoost used native categorical handling. Missing values were managed using mean imputation for Support Vector Regression, median imputation for Random Forest, and XGBoost's built-in missing-value handling.

Model Development and Evaluation

Support Vector Regression, Extreme Gradient Boosting, and Random Forest models were trained using an 80/20 chronological train-test split (178/45 observations). Model robustness was further evaluated with 5-fold TimeSeriesSplit cross-validation. Performance was assessed using R^2, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

Results

Model Performance

All three models yielded meaningful predictions of CPTRT from physiological and demographic predictors. Support Vector Regression achieved the highest single-split R^2 (0.79, MAE = 29.33 ms, RMSE = 39.64 ms). Five-fold time-series cross-validation revealed that Random Forest demonstrated the most temporally consistent performance (CV R^2 = 0.68, SD = 0.04), followed by XGBoost (CV R^2 = 0.63, SD = 0.07) and Support Vector Regression (CV R^2 = 0.57, SD = 0.11). The substantially lower cross-validation variance of ensemble methods indicates superior generalisation across temporally heterogeneous deconditioning windows. Predicted-versus-observed plots are shown in Figure 1 and full performance metrics are presented in Table 1.

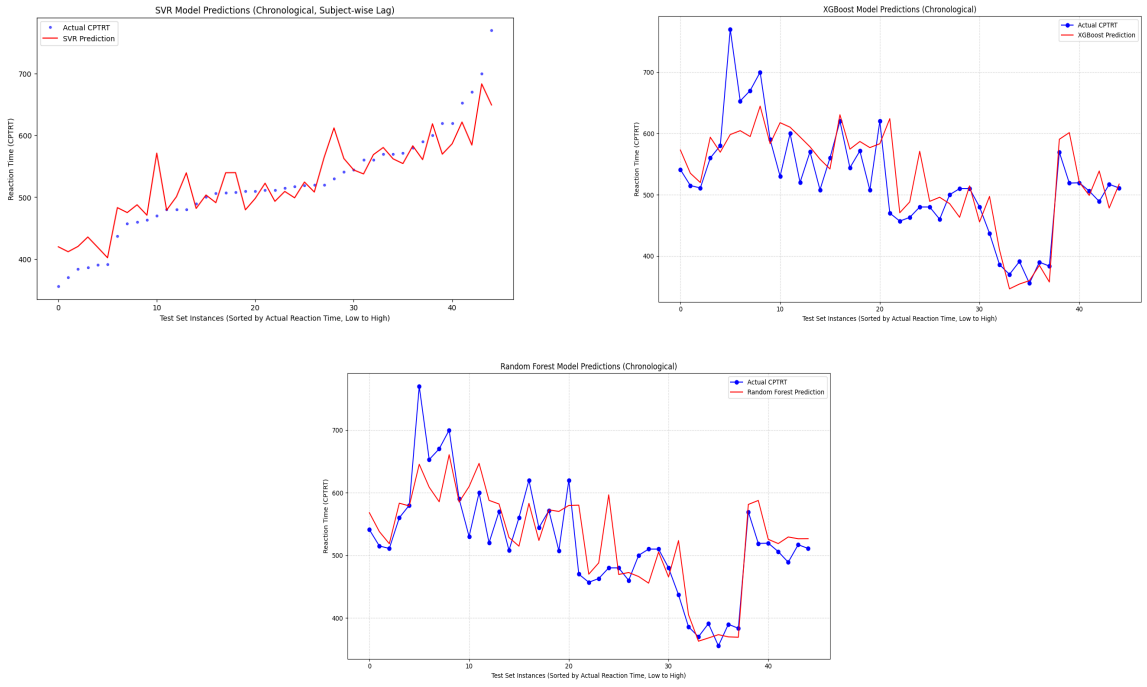

Figure 1. Predicted versus observed CPTRT values across the chronological test set (n = 45) for each model: (a) Support Vector Regression, sorted by ascending actual reaction time; (b) XGBoost, sorted chronologically by test session; (c) Random Forest, sorted chronologically by test session. Blue lines/dots represent observed CPTRT; red lines represent model predictions.

Table 1. Model performance under chronological 80/20 splitting with subject-wise lag features (n = 223).

Model	R^2	MAE (ms)	RMSE (ms)	CV R^2 (mean)	CV (SD)
SVR (linear)	0.79	29.33	39.64	0.57	0.11
XGBoost	0.63	37.31	52.14	0.63	0.07
Random Forrest	0.70	34.69	46.83	0.68	0.04

Discussion

The present findings support the feasibility of using peripheral physiological markers to estimate cognitive performance changes during spaceflight-analogue deconditioning. Support Vector Regression demonstrated superior accuracy on the chronological test set, whereas Random Forest showed lower cross-validation variance, indicating stronger temporal generalisation. This suggests that linear models may be more sensitive to temporal distribution, while ensemble methods better accommodate non-stationary physiological-cognitive relationships. The consistent importance of CPTRT lag indicates a strong autoregressive component in cognitive performance. Monosynaptic reflex latency (MTSRT) and cardiac demand indicators also emerged as relevant predictors, consistent with neuromuscular and haemodynamic influences on processing efficiency. These findings provide preliminary support for physiological markers in cognitive monitoring, warranting validation in larger longitudinal cohorts and additional spaceflight analogue environments.

Disclosures

The authors declare no conflicts of interest. Data used in this study are publicly available through the NASA Life Sciences Data Archive (https://lsda.jsc.nasa.gov). The work has been supported by Engineering Accelerated and Tom Yim scholarship.

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