Intuitive Human-in-the-Loop Control for Medical Cyber-Physical Systems

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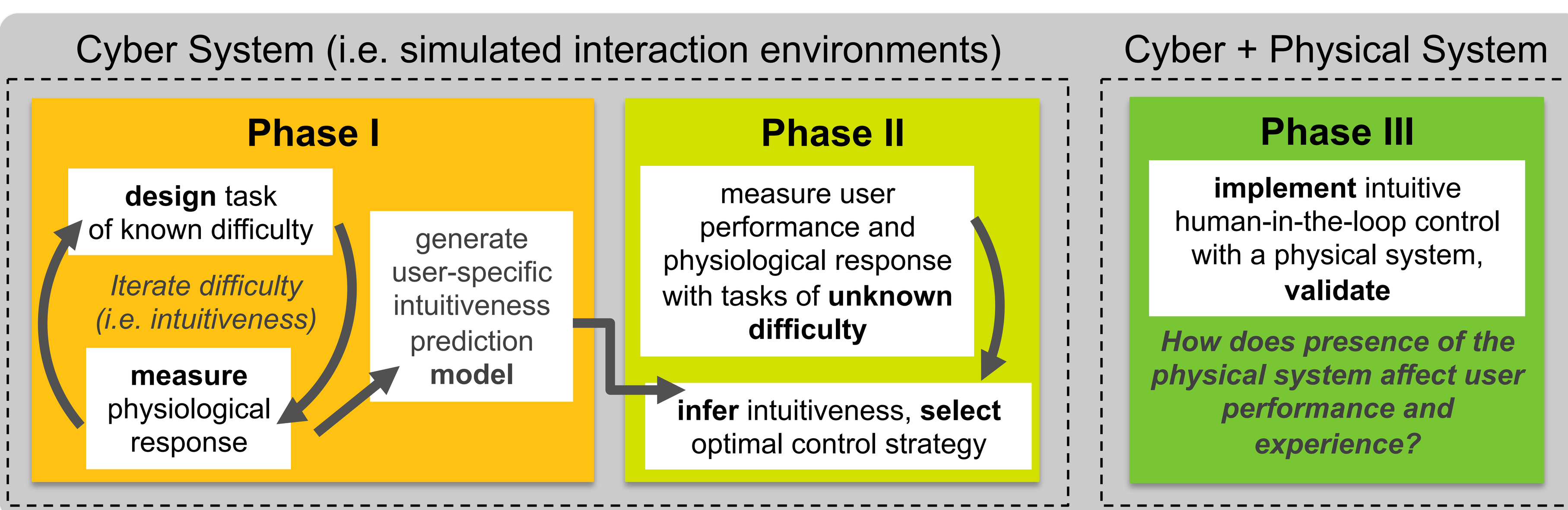
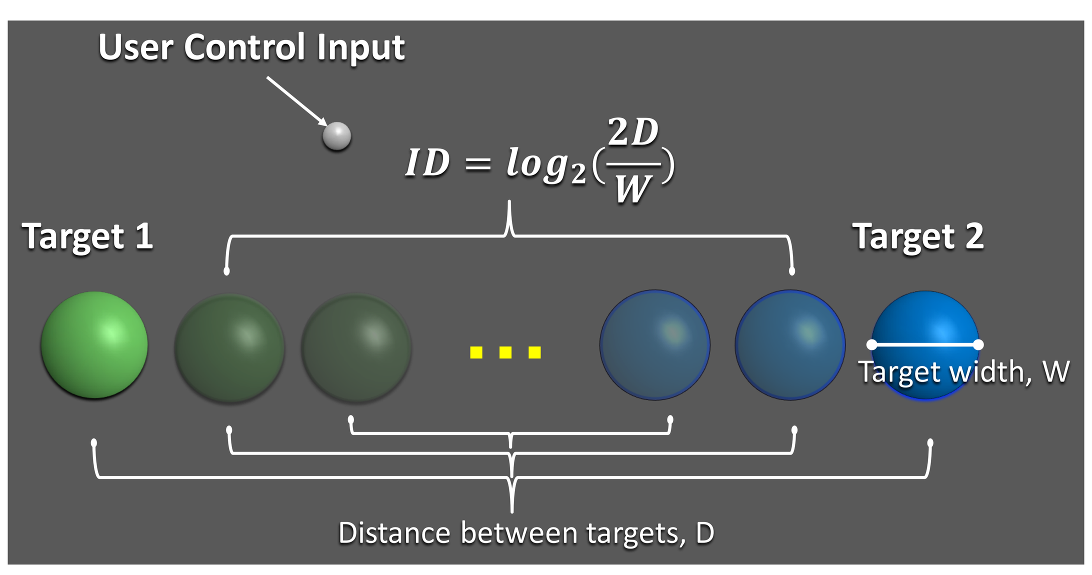
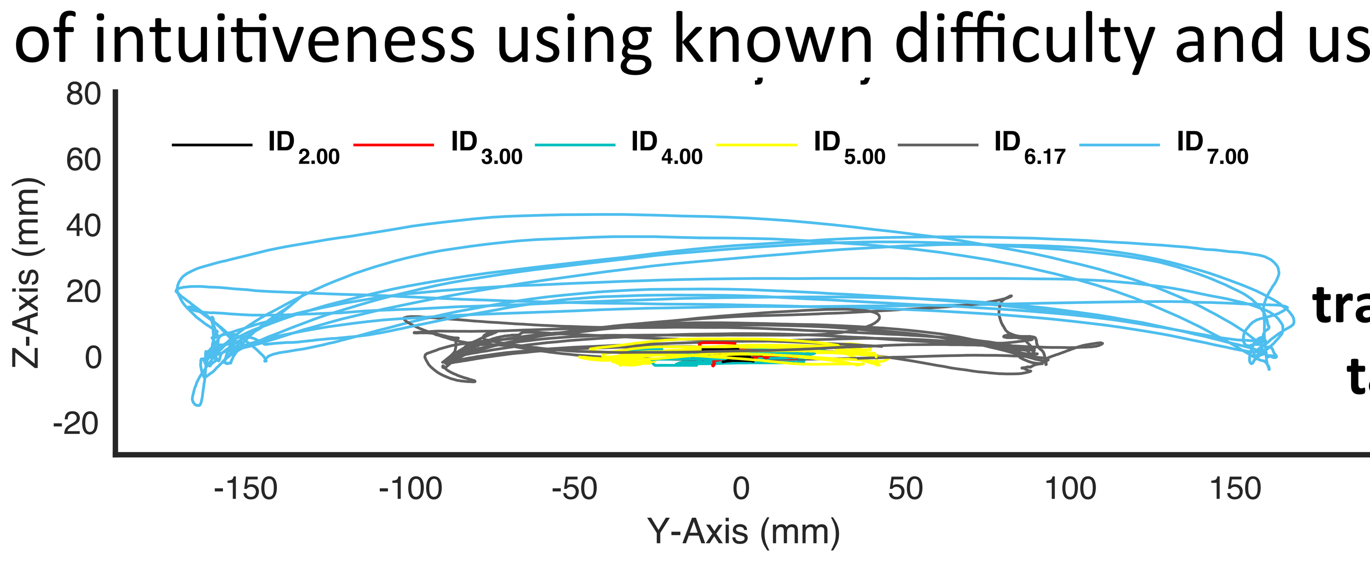
Overall Research Strategy



Designing a Task of Known Difficulty

Fitts' Law is a psychomotor relationship between the time (T) to move between targets of distance (D) apart, and width (W). We conducted a human user study *(UTD IRB #14-57)* to build models of intuitiveness using known difficulty and user response.

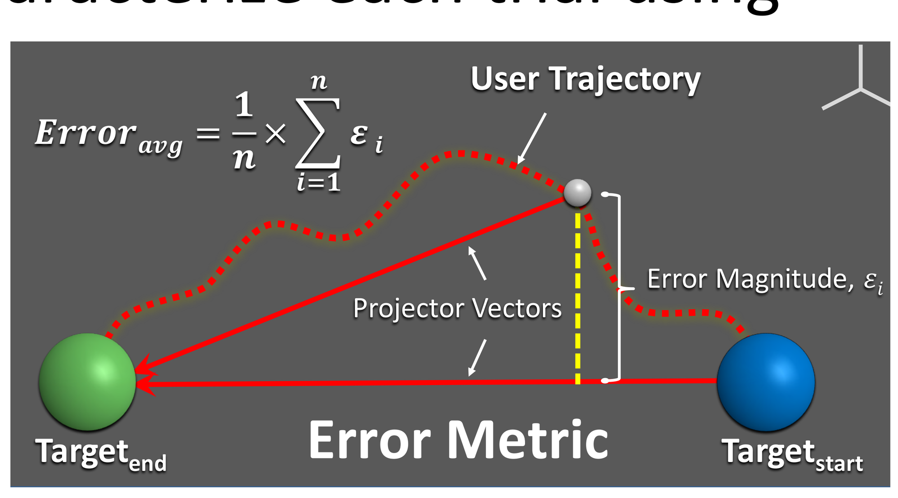




Example user trajectories for all task difficulties

Obtaining Metrics from Experimental Tasks

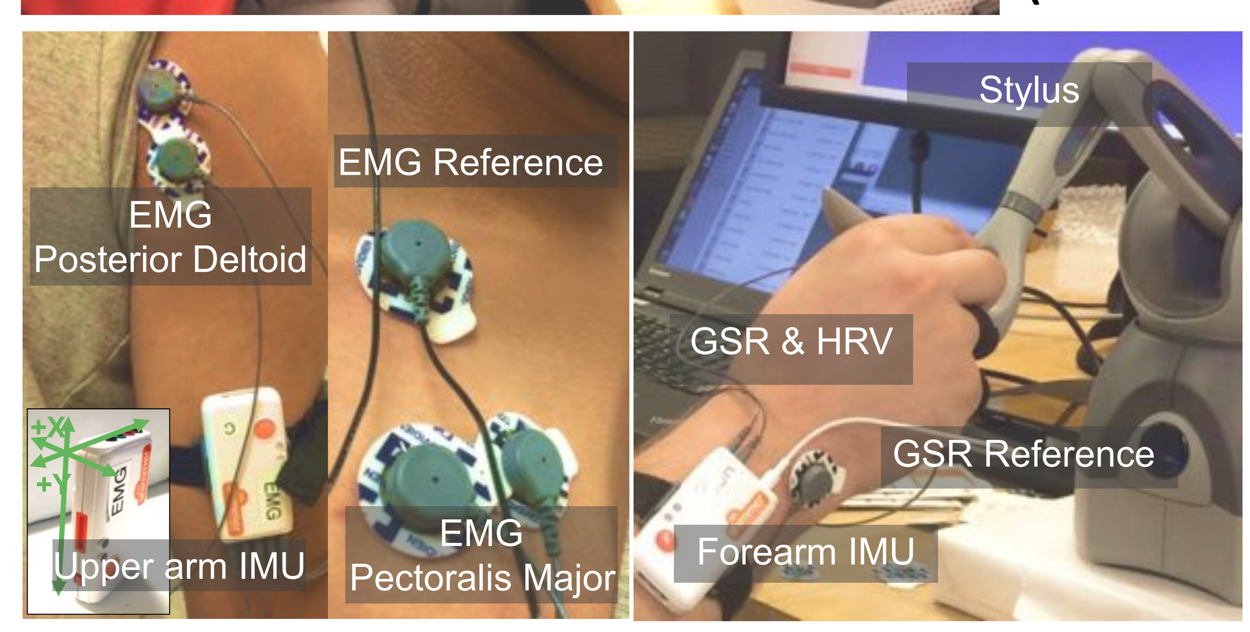
We identified 17 metrics to characterize each trial using performance, kinematic, and physiological data. Metrics include: muscle activation, cognitive state, heart rate variability and GSR peak mag.



Phase I: Sources of Intuitiveness

Sensor Integration to Measure Intuitiveness

To measure user performance and physiological response, we are integrating sensors such as IMUs with electromyography, skin galvanic response, and heart rate measurements (Shimmer Sensing) and an EEG headset (Biopac) with custom C++ code to control a haptic device, using the Robot Operating System (ROS).



Intuitiveness Model

A least-squares intuitiveness model was developed using the experimental metrics for tasks of known difficulty. Four models were tested, including: all metrics (Model I), metrics correlated to task difficulty (Model II), and two equal rank models missing performance metrics (Model III) and kinematic metrics (Model IV).

$$Y_i = \beta_0 + \sum_{i=1}^{\omega} \beta_j X_{i,j} + \varepsilon_i$$

$$i = 1, \cdots, \upsilon; \quad j = 1, \cdots, \omega$$

Known Difficulty

$$\boldsymbol{Y} = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_\upsilon \end{pmatrix} = \begin{pmatrix} ID_1 \\ ID_2 \\ \vdots \\ ID_\upsilon \end{pmatrix}$$

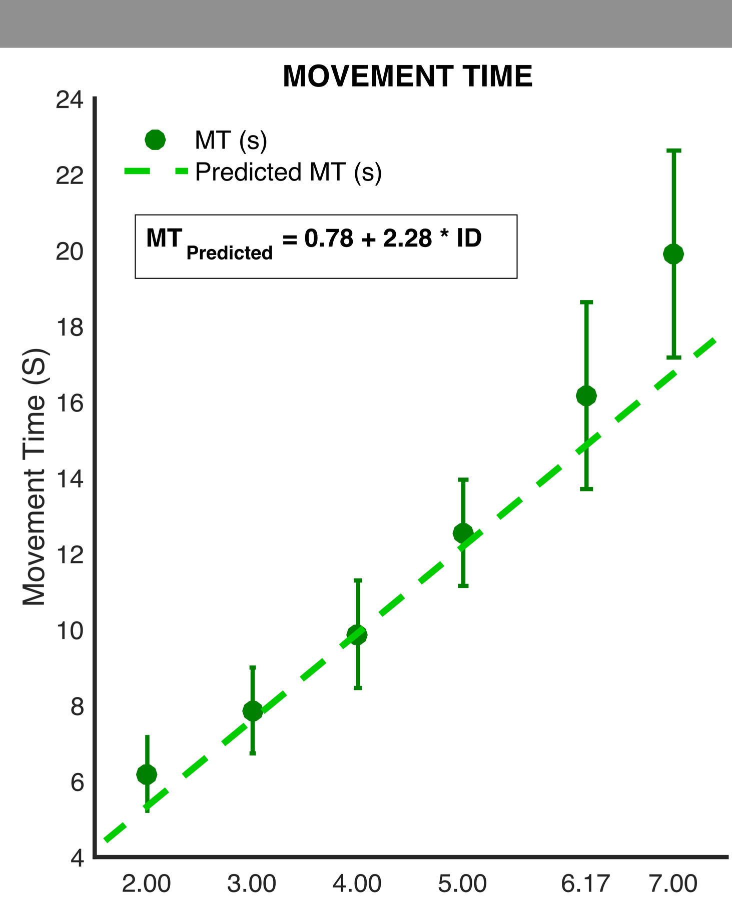
Regression Coef.

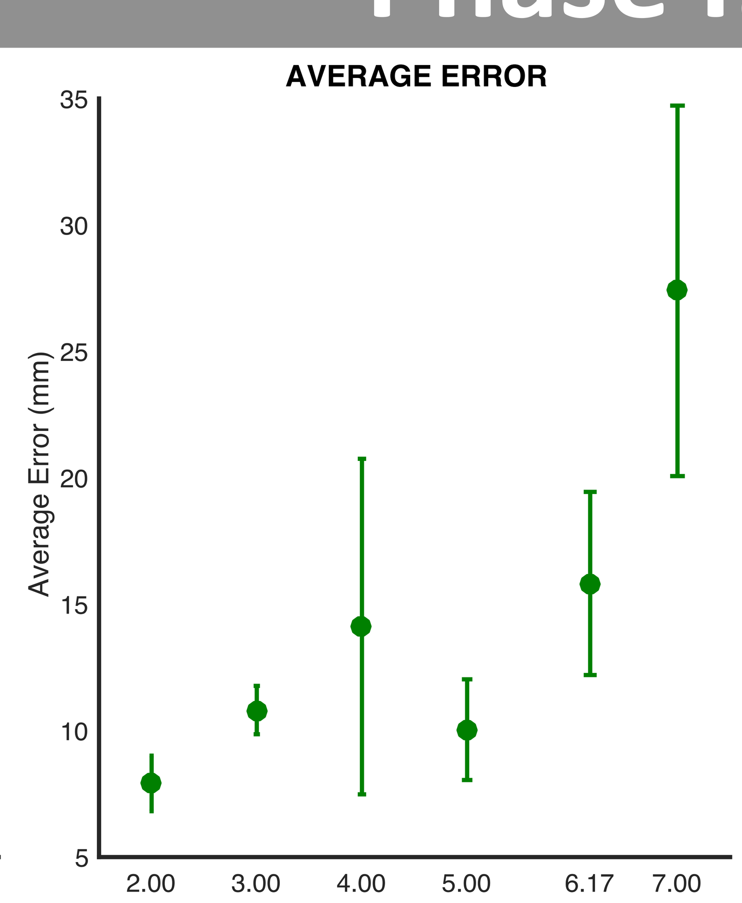
$$\boldsymbol{\beta} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_\omega \end{pmatrix}$$

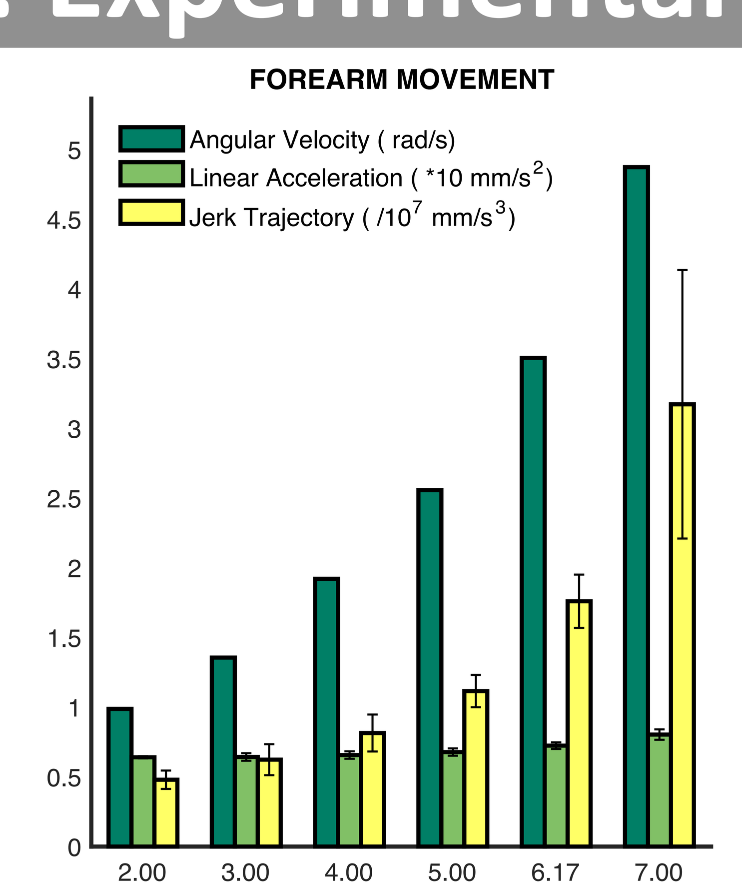
Sensor data

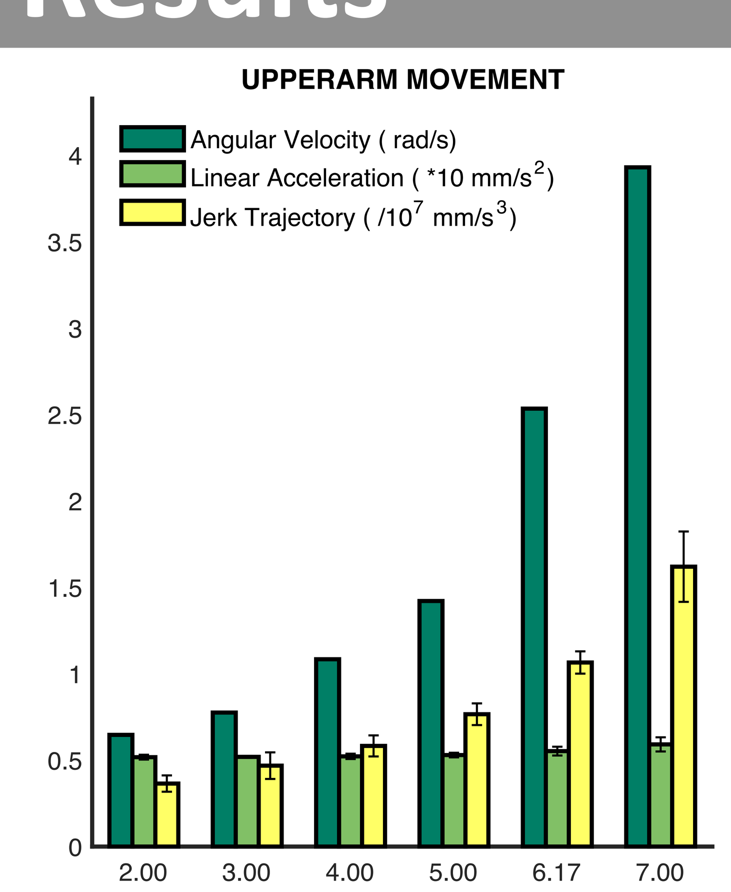
$$\boldsymbol{X} = \begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_\omega \end{pmatrix} = \begin{pmatrix} x_{11} & \dots & x_{1\omega} \\ x_{21} & \dots & x_{2\omega} \\ \vdots & \ddots & \vdots \\ x_{\upsilon 1} & \dots & x_{\upsilon\omega} \end{pmatrix}$$

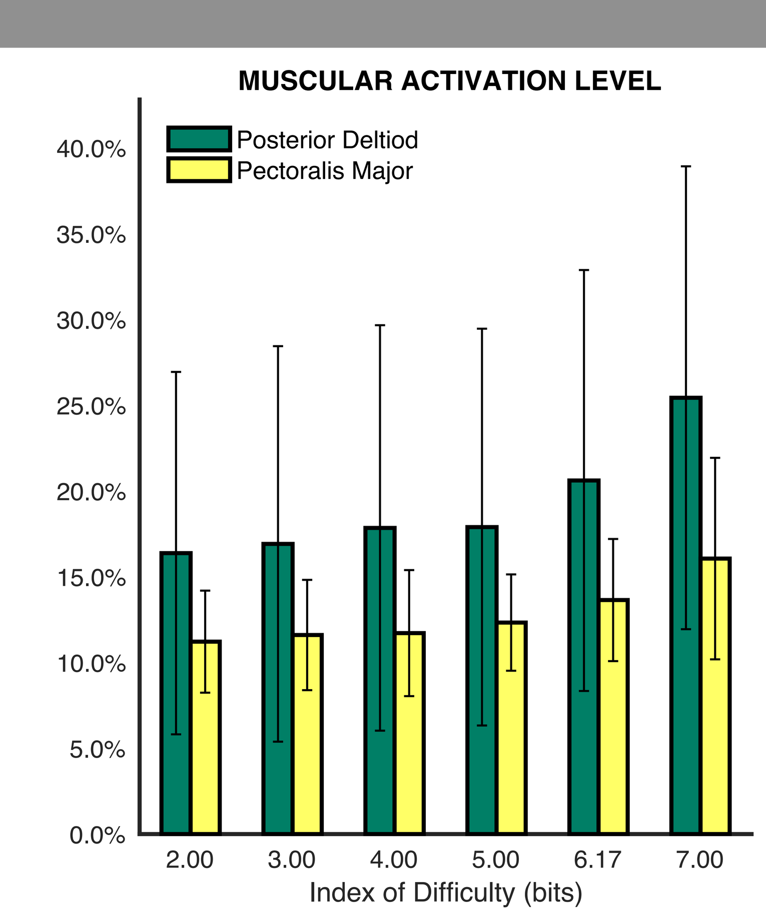
Phase I: Experimental Results











Results and Discussion: All metrics correlated significantly ($p<0.05$) with task difficulty, with the exception of EEG cognitive state metrics and the GSR peak magnitude. All models had a task difficultly prediction error of less than 10%, with Model I having the smallest prediction error (4.81%) across all subjects and trials. Furthermore, Models II, III, and IV did not have statistically different prediction errors, indicating that not only can several models be used to predict task difficulty, but also that knowledge of the specific task is not required.