

# Evaluating a cost-effective wireless, wearable brain-computer interface for guided motor imagery

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## BACKGROUND

- **Stroke** remains the second-leading cause of death and the third-leading cause of death and disability combined in the world (Feigin et al., 2022).
- Upper limb impairment is a common symptom among stroke. Motor Imagery (MI) activates many of the same brain areas as those involved in motor execution (Hardwick et al., 2018), and may facilitate neurorehabilitation after stroke.
- Unsupervised **at-home BCIs** may increase clinical use by reducing the burden on healthcare providers and increasing patient • agency.
- Recent technological advances have allowed for a **brain-computer interface (BCI)** to provide feedback on motor imagery based on signals gathered using a wireless, wearable EEG cap.
- Wireless EEG in combination with a BCI has the potential to be used independently by stroke survivors in their own homes without expert supervision.
- The effectiveness of commercially-available wireless EEG caps has not been fully tested for this application.
- Clinical trials using Brain-Computer Interface (BCI) for stroke rehabilitation have shown promising results, yet clinical adoption is



Classification accuracy scores for a total of 380 experimental blocks were analysed. Overall participant accuracy scores tended to fall at the 50% or chance level. There was some score variation but it did not rise over time. Descriptive results for this data are shown below in Table 1 and Figure 3. Table 1

Descriptive Results Across Each Training Session

| Session Number | M     | SD   |
|----------------|-------|------|
| 1              | 50.79 | 1.67 |
| 2              | 50.00 | 0.63 |
| 3              | 50.00 | .27  |
| 4              | 50.42 | 1.43 |
| 5              | 50.17 | 0.61 |
| 6              | 50.33 | 0.38 |
|                |       |      |

Figure 3

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Line Graph of Classification Accuracy over Time

lacking (Simon & Ruddy, 2021)

The present study examines the feasibility of using a BCI feedback loop to improve Kinesthetic MI (KMI) control in healthy participants. We used the EMOTIV EPOC X headset in combination with a computer-based task to form a BCI.

This task required participants to generate KMI for right- and left-hand movements. Feedback was provided in the form of classification accuracy of brain signals for these two movement conditions (right-versus left-hand movement). The primary hypothesis was that this <u>classification accuracy would increase over time as a result of participants</u>

learning to control the BCI.

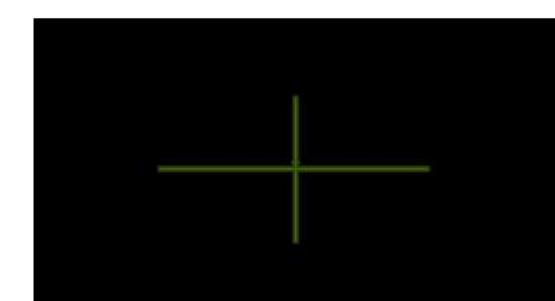
## **METHODS**

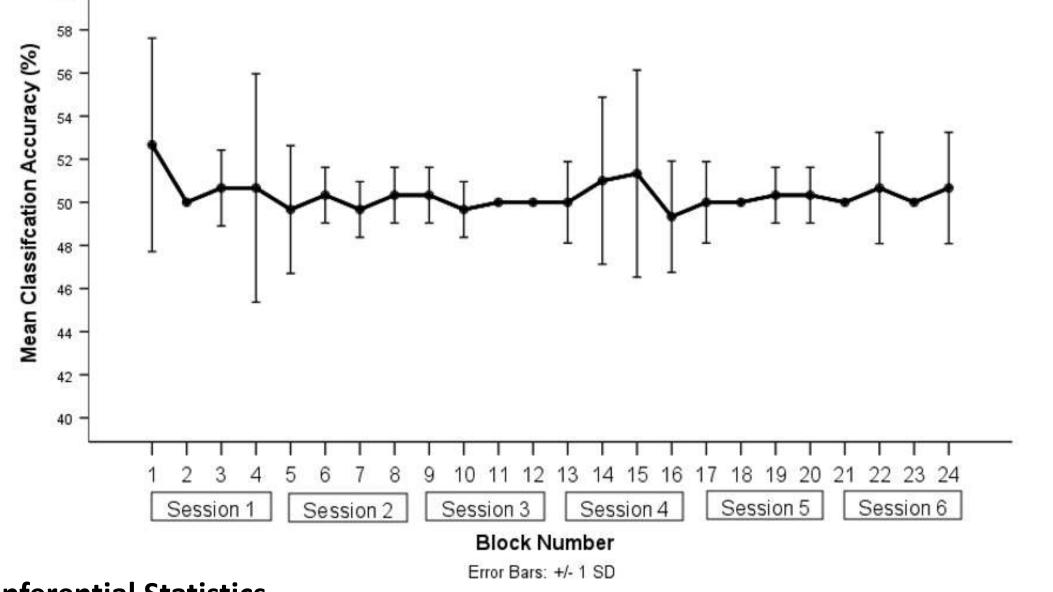
- 19 participants >18 years with no neurological or physiological conditions that would affect the EEG or their performance of the motor imagery task.
- The wearable EEG cap the Emotiv EPOC X with 14 channels and saline-soaked pads.
- The location of the motor cortex was approximated on each participants head before placing the cap to ensure that one electrode sat over this location. Participants were instructed to a imagine the feeling of making of a specific and forceful hand movement using their left or right hand.

#### Figure 1

the calibration block of the experiment the computer screen displayed a green fixation cross (for 7 seconds), and in each trial a red arrow appeared on one side of the cross (for 5 sec). The direction of the arrows (left or right in a random order) indicated which hand participants should imagine moving. (Figure 1)

Experimental Stimuli in Calibration Phase





#### **Inferential Statistics**

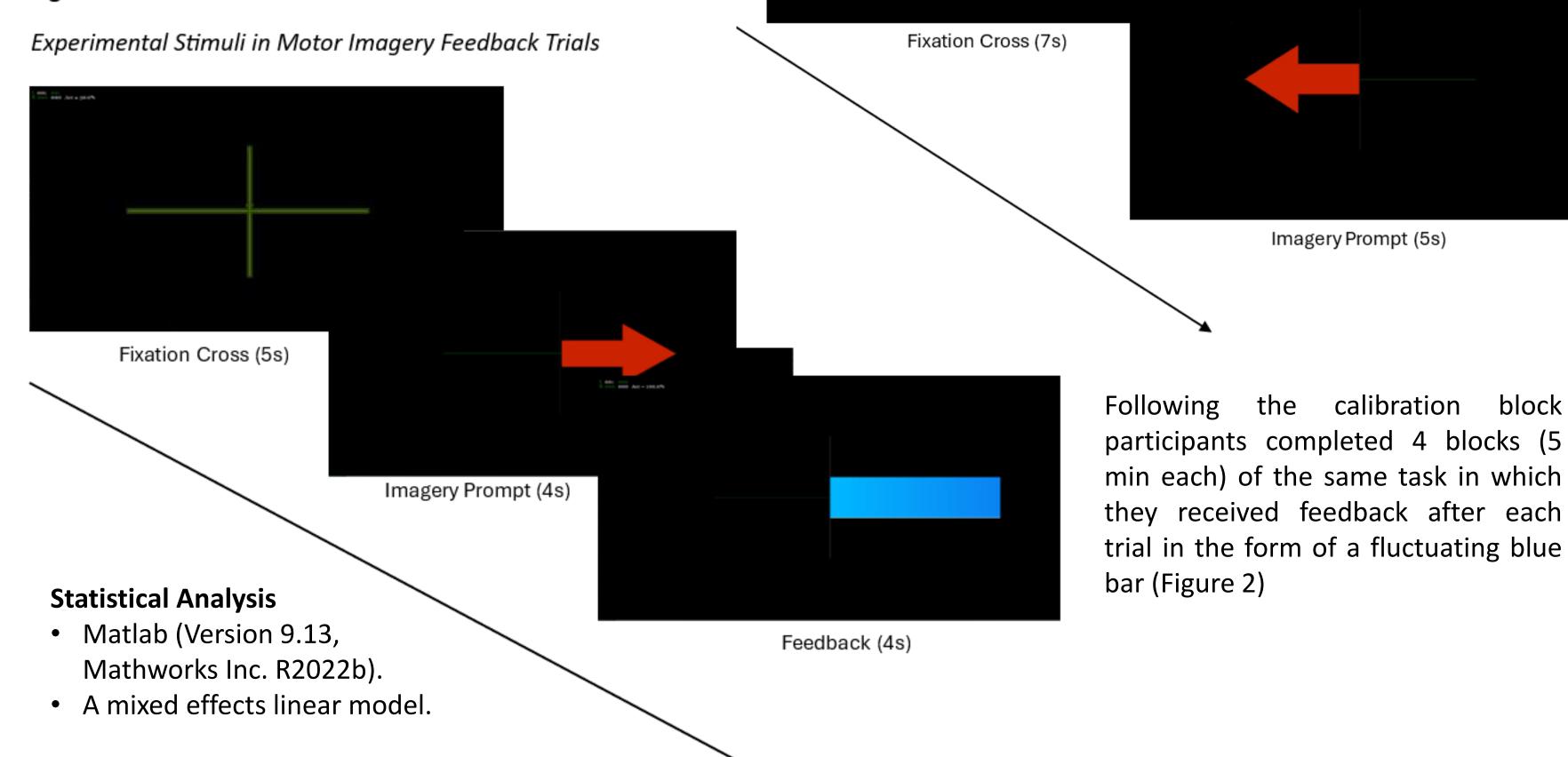
A mixed effects model was conducted on the data. All participant scores were included in this model, including those who completed only one or two sessions. Classification accuracy was modelled with block number as a fixed effect and individual participant as a random effect. This analysis indicated that practice over time did not have a significant effect on classification accuracy

(b = -.0152, p = .388, 95% CI [-0.05, 0.02]).

## wireless EEG headsets



Figure 2



#### **BCI operation**

A common spatial pattern algorithm was used to extract relevant EEG frequency bands for each motor imagery category. The EEG signals were filtered in an alpha/beta 8-30 Hz range using a high-pass 5th order Butterworth band-pass filter. The filtered signals were split into segments every 16th of a second. Linear discriminant analysis was used to classify signal patterns for right- and left-hand motor imagery. The outcomes of this analysis were used to display feedback on the screen during the

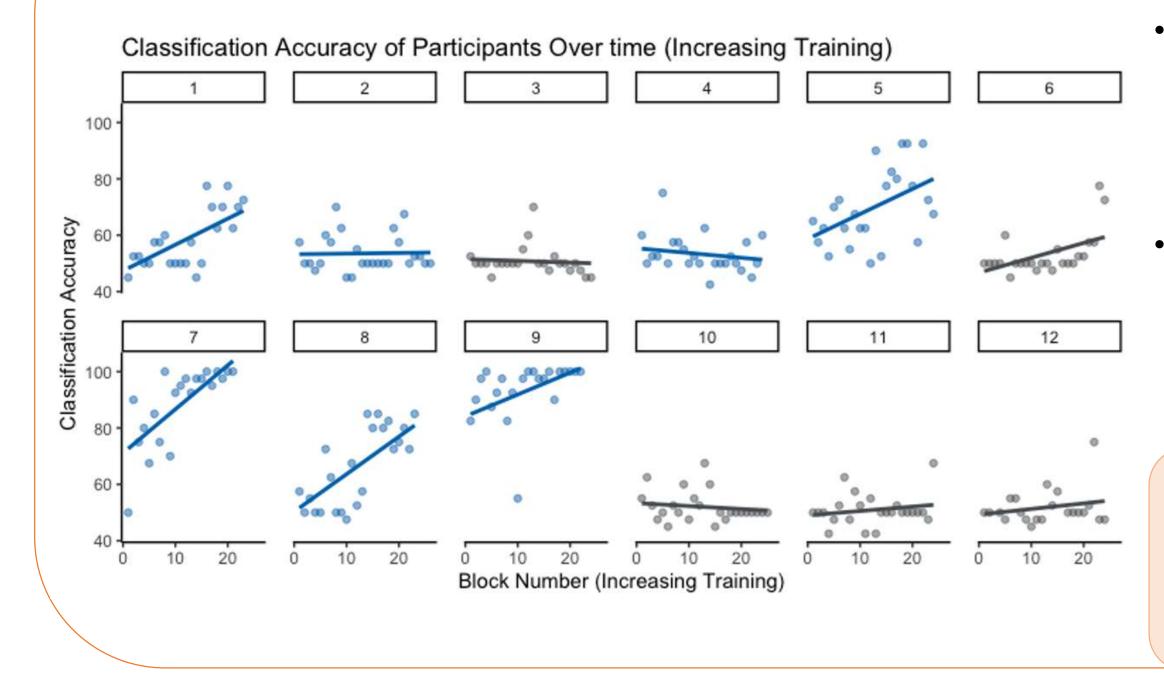
task.

## **CONCLUSION**

- A mixed effects model indicated that there was no significant improvement in classification accuracy over time. This result indicates that the EEG cap the EMOTIV EPOC X is not sufficiently sensitive to differentiate between brain signals associated with two motor imagery conditions. As such we concluded that it was not suitable for BCI-based motor imagery training for stroke patients.
- In a previous study using the same protocol Simon and Ruddy (2022) explored the feasibility of using a wireless EEG cap (a dry electrode, 16 channel, Cumulus) and BCI for neurorehabilitation. And participants were capable of gaining control over the BCI using motor imagery over 6 daily sessions at home and with minimal supervision. So, it is possible to obtain control (improving CA) over an in-home BCI using a 16-electrode, wireless, EEG system.

These results suggest that wireless EEG equipment and BCI technology require further development before they can be used in at-home stroke rehabilitation

## **Comparison with previous results (Simon & Ruddy, 2022)**



• A wireless EEG cap (a dry electrode, 16 channel, Cumulus) was tested for in-home BCI training with 12 healthy participants. They undertook 6 days of EEG BCI training within their homes, receiving remote online instructions.

block

- The BCI used common spatial patterns (CSP) and linear discriminant analysis (LDA) to classify mental states and provide feedback. The primary outcome was online classification accuracy of the mental state during BCI performance.
- Participants achieved control (58% average CA) over the BCI in 7 out of 12 cases
- Over time controllers produced more distinct and lateralized patterns of neural activity.

#### interventions.

## References

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