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School of Psychological and Cognitive Sciences and Beijing Key Laboratory of Behavior and Mental Health, Peking University, Beijing 100871, China
Center for Brain and Cognitive Sciences, Peking University, Beijing 100871, China
Key Laboratory of Machine Perception (Ministry of Education), Peking University, Beijing 100871, China
PKU-IDG/McGovern Institute for Brain Research, Peking University, Beijing 100871, China
Department of Psychology, Arizona State University, Tempe, AZ 85287, United States

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ABSTRACT

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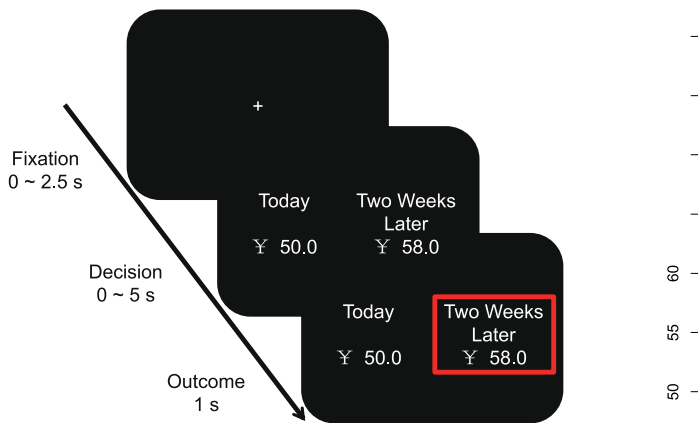
Introduction

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Intertemporal choice (ITC) task

Materials and methods

Participants



$$SV = LL \text{ Amount} / (1 + kD)$$

k

f_l

f_i

k

k

f_i

f_i

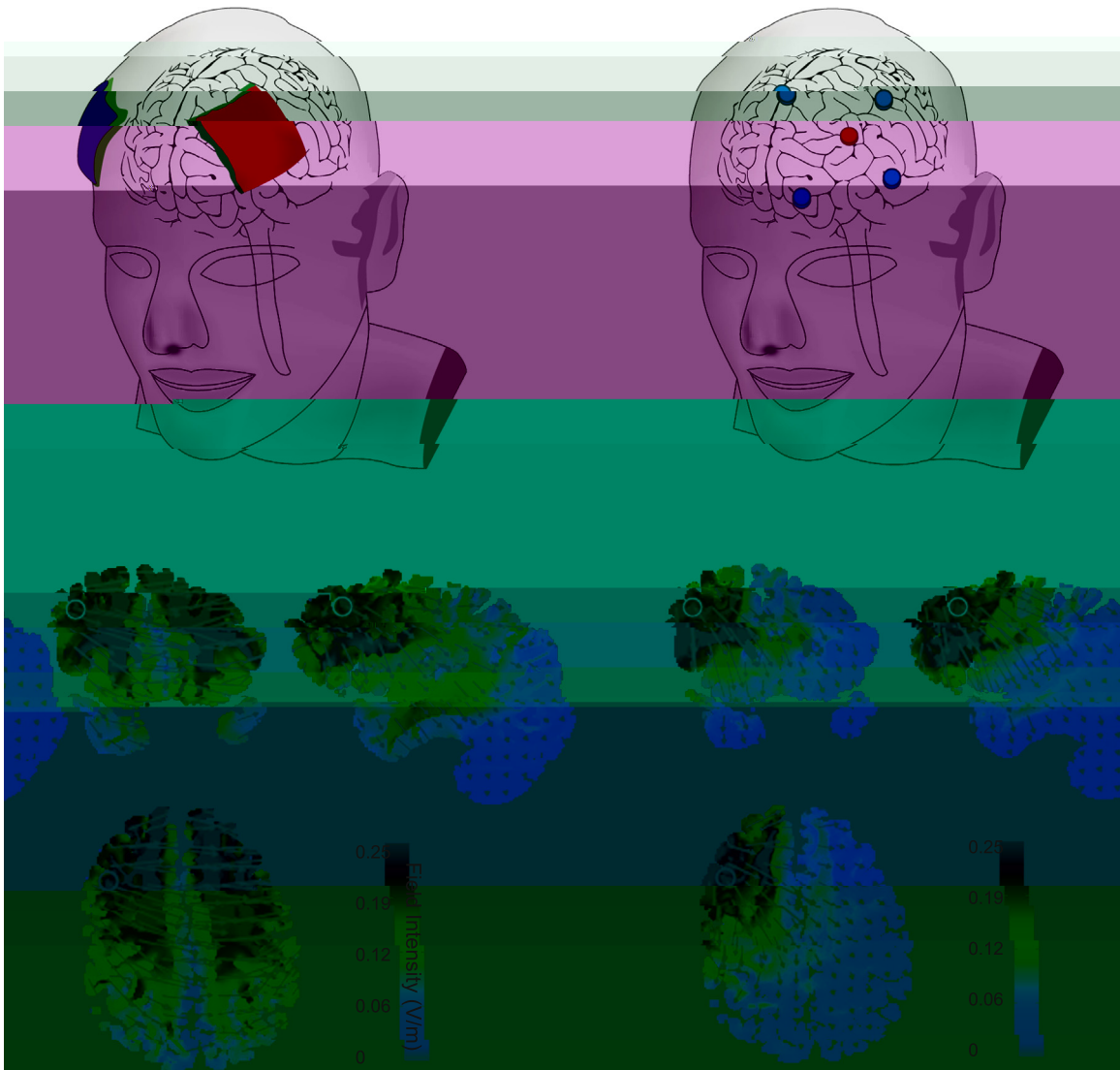
Procedure

=:

f_l

+ -

- +



Conventional tDCS

Behavioral data analysis

$$\text{logit } P(\text{choose LL}) = \beta_1 \text{ LL amount} + \beta_0$$

$$\text{logit}(0.5) = \beta_1 \text{ indifference point} + \beta_0$$

$$\text{indifference point} = -\beta_0 / \beta_1$$

HD-tDCS

$$SV = \frac{A}{1 + kD}$$

$$SV_{ASAP} = g(D_{ASAP}) \frac{A}{1 + k_{ASAP}(D - D_{ASAP})}$$

$$g(D_{ASAP})$$

$$k \sim N(\mu, \sigma)$$

$$P(\text{choose LL}) = \frac{1}{1 + e^{-b(SV_{LL} - SV_{SS})}}$$

$$b$$

“ k fi ”

Results

Immediate context

Experiment 1.

$+ \quad - \quad - \quad +$
 $k \quad + \quad - \quad - \quad +$

$p = ; \quad \text{fi} \quad F = \quad \eta^2 = \quad F = \quad \eta^2 =$
 k

$F = \quad \eta^2 = \quad p =$

Experiment 2A and 2B.

$+ \quad +$
 k

$\eta^2 = \quad p = \quad F = \quad \eta^2 = ;$
 $p < \quad \text{post-hoc}$

$F = \quad \eta^2 = \quad \text{fi} \quad p = \quad t$
 $+ \quad +$

$\Delta = - \quad - \quad t = - \quad \Delta = - \quad + \quad = - \quad +$
 $= - \quad p = \quad = - \quad ; \quad = - \quad - \quad t$
 $t = \quad p = \quad \Delta = \quad ; \quad = -$

$\eta^2 = \quad k \quad \text{Post-hoc} \quad t \quad F =$
 $p = \quad k \quad k = - \quad + \quad + \quad +$
 $= - \quad p = \quad \Delta \quad k = - \quad ; \quad + \quad \Delta \quad k = - \quad ; \quad =$
 $- \quad - \quad t = - \quad p = \quad ; \quad \Delta \quad k = \quad ;$
 $= - \quad t = \quad p =$

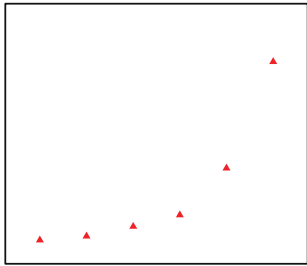
k

$+ \quad +$

$- \quad -$

$F = \quad \eta^2 = \quad F = \quad \eta^2 = ; \quad p =$
 $t \quad p <$

$F = \quad \eta^2 = \quad \text{fi} \quad p =$



Delayed context

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$p = \dots$ $p = \dots$ $p = \dots$

Discussion

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$$\eta^2 = \frac{F}{p} = \frac{F}{p} ; \eta^2 = \frac{F}{p} = \frac{F}{p} ; \eta^2 = \frac{F}{p} = \frac{F}{p}$$

$$F = \eta^2 p = \eta^2 p ; F = \eta^2 p = \eta^2 p ; F = \eta^2 p = \eta^2 p$$

$\times \times$

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$$p = \dots ; p = \dots ; p = \dots ; \times$$

\vdots

\vdots

et al.

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Conclusion

The study has shown that the proposed method is effective in identifying and classifying the different types of faults in the power system. The results of the simulation show that the proposed method is able to detect and classify the faults with high accuracy and speed. The proposed method is also able to handle the complex and non-linear nature of the power system. The proposed method is a promising approach for fault diagnosis in power systems.

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Appendix A. Supporting information

Additional supporting information can be found in the online version of this article, which is accessible at <https://doi.org/10.1112/jee.12345>.

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