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How to measure attention in remote video-based learning – and can we improve attention with interactive viewing?

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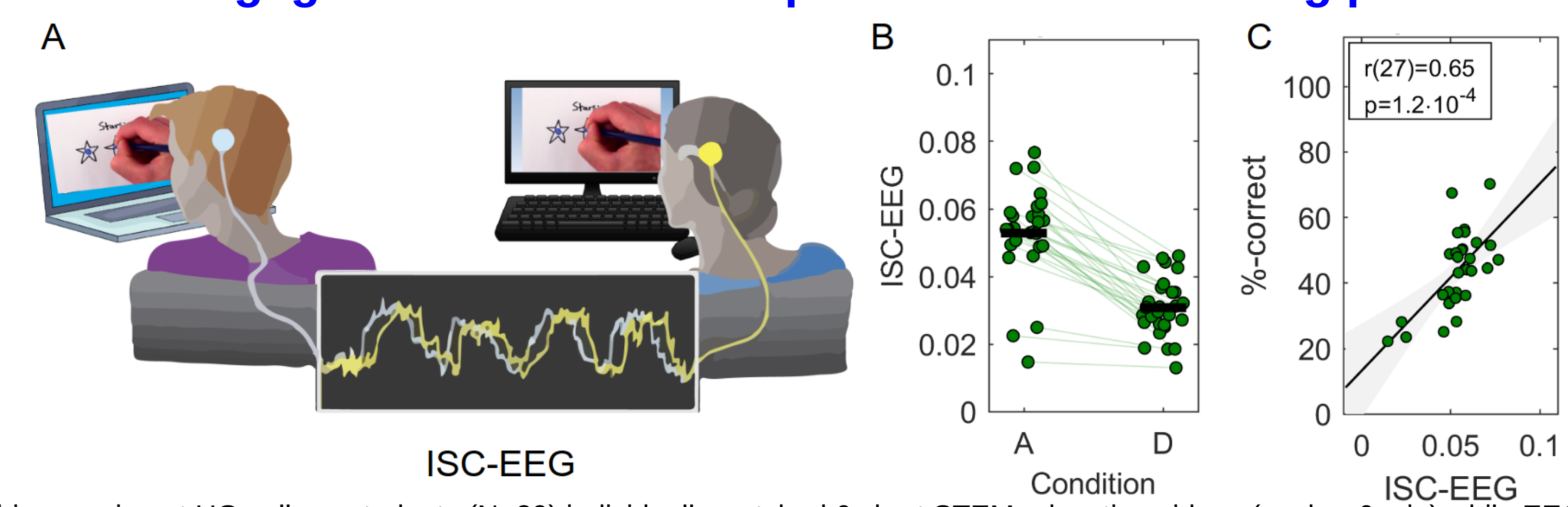
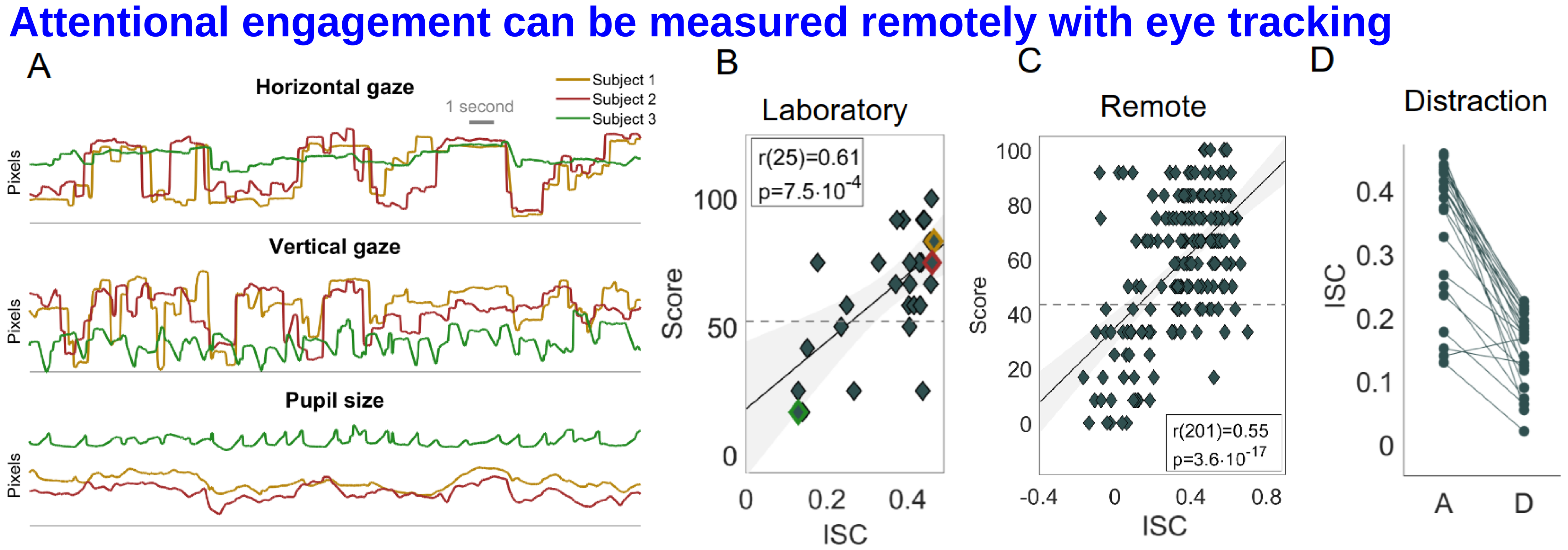
Summary: Education is moving online. During the global pandemic this ongoing process accelerated and educators leveraged existing online video content to supplement synchronous remote instruction. However, passive viewing of video often fails to engage students. We hypothesized that the level of attention to online video is predictive of the information student manage to retain. To test this, we measured eye gaze position in remote experiments, and electroencephalography in the laboratory. We use inter-subject correlation of these signals as a validated metric of attentional engagement with the video. We used dynamic and well-produced content that is widely available online for STEM disciplines. Results demonstrate that attention is not equally engaged across students, and that this is predictive of individual learning performance. Additionally, we prospectively tested interventions that aim to promote active viewing on an online platform . We find that interleaving questions, allowing rewind, and providing feedback all improve performance. However, these interventions came at a cost of additional time investment of the learner, which only helped low performing individuals. Future experiment will test additional intervention that promote active viewing, and will test the hypothesis that performance gains are mediated by enhanced attentional engagement with the videos.

Attentional engagement with video is predictive of test taking performance



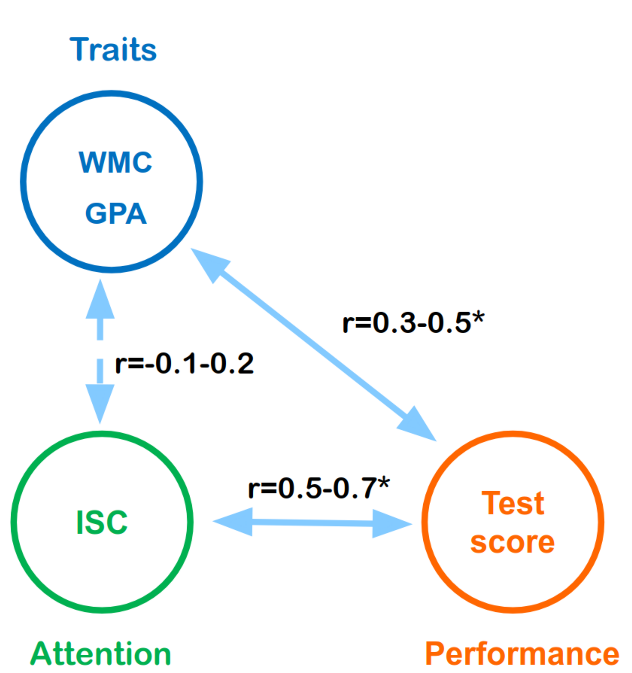
(A) In this experiment UG college students (N=29) individually watched 6 short STEM education videos (each < 6 min) while EEG was recorded. Afterwards, students answered test questions about the material. (B) Inter-subject correlation of EEG while watching the video (ISC-EEG) is strongly modulated by attention (A - normally attending to the video, D - distracted by a mental arithmetic task). (C) ISC-EEG in the attentive condition is predictive of performance in a subsequent test. Note that 3 students were not attentive in the A condition; they performed poorly on the test. Results for "Stars" video here (3:28 min) are similar for the 5 other videos. (Madsen, PNAS Nexus, 2022).

Attentional engagement can be measured remotely with eye tracking



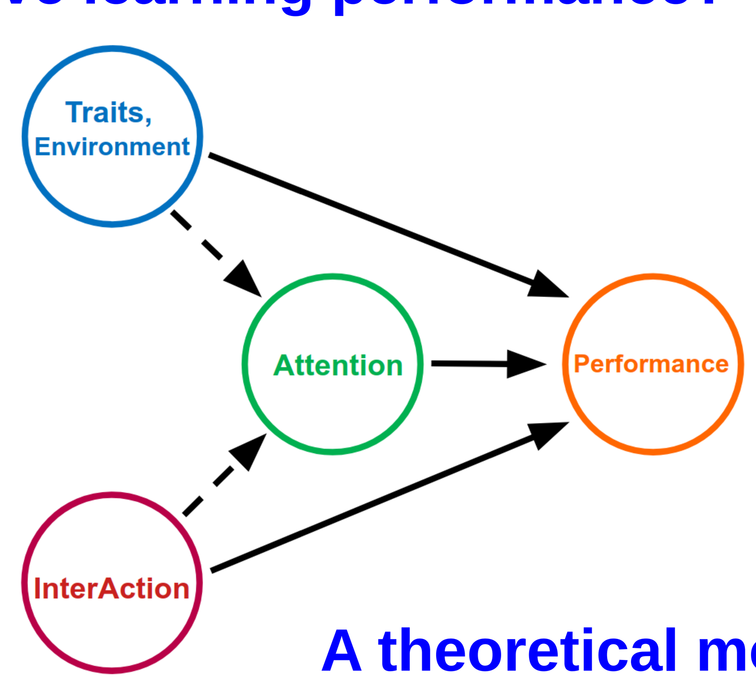
(A) Eye position traces as well as pupil size over 20 seconds during video presentation. Data is shown for three subjects recorded in the laboratory (N=27 total). Subjects 1 and 2 show high ISC, whereas subject 3 does not. (B) ISC-eye correlates with test scores in a subsequent exam on the material that was presented in the video. Subjects 1 and 2 (highlighted in red and orange color) perform well, Subject 3 (green) does not. (C) The same experiment was performed online recruiting subjects on Prolific using conventional web cameras to measure eye movements. ISC-eye is measured for each of N=203 subjects by correlating with the median eye/pupil traces recorded in the lab (i.e. traces from the remote subjects do not need to be transmitted). (D) After viewing the video attentively (A - attentive) students view the same video again but are now distracted by a mental arithmetic task (D – distracted). (Madsen, PNAS, 2021)

Attentional state and individual traits correlate with test scores.



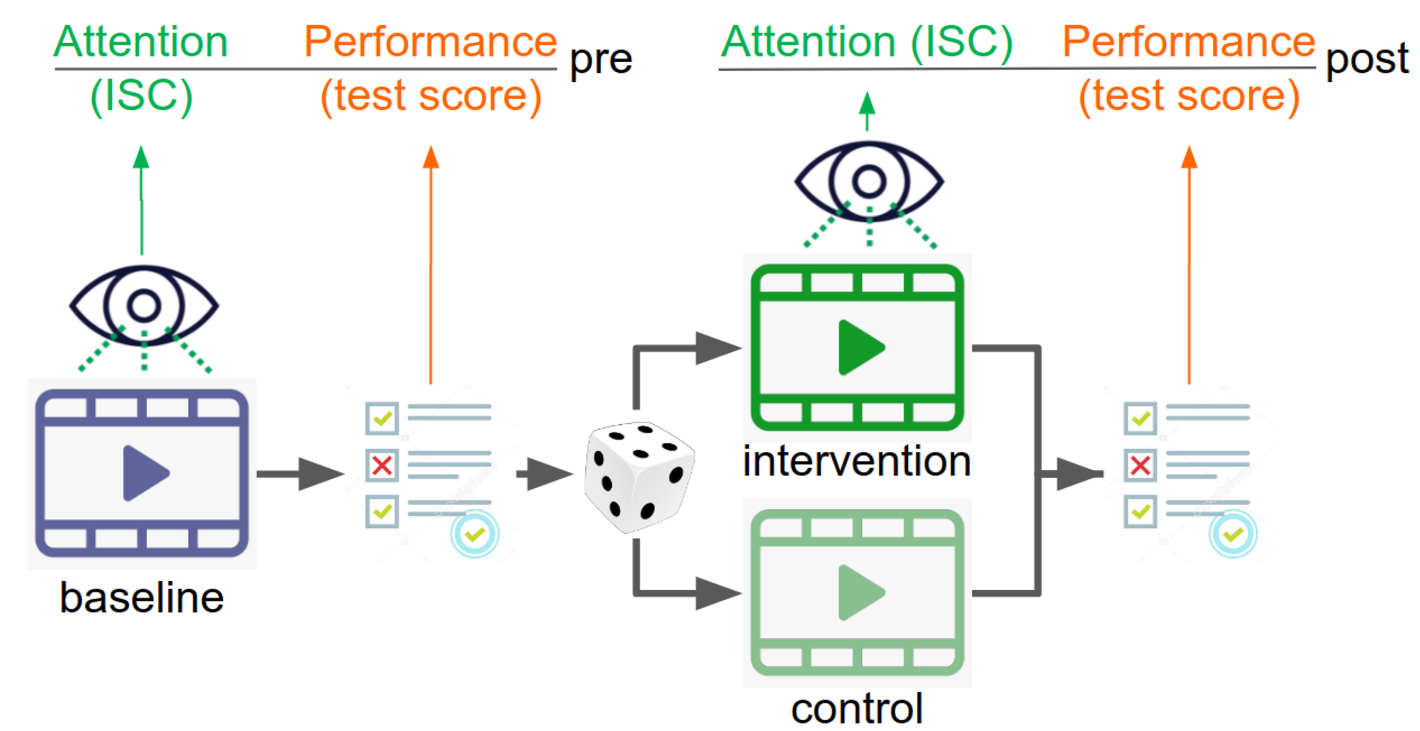
Correlation coefficient (r) across students indicated as light blue arrows (* p<0.05). Attentional engagement is measured as ISC-EEG during passive viewing of the videos. Performance is measured as a test score with multiple choice questions about material presented in those videos. Individual student traits here were limited to working memory capacity (WMC; measured with the DigitSpan task) and grade point average (GPA in their UG major).

Can we add interaction to video to improve learning performance?



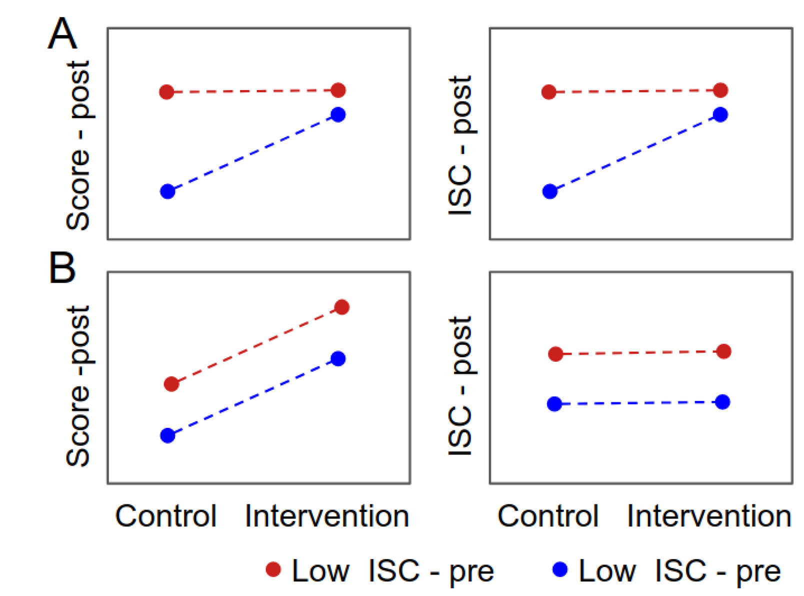
A theoretical model

Experimental design:



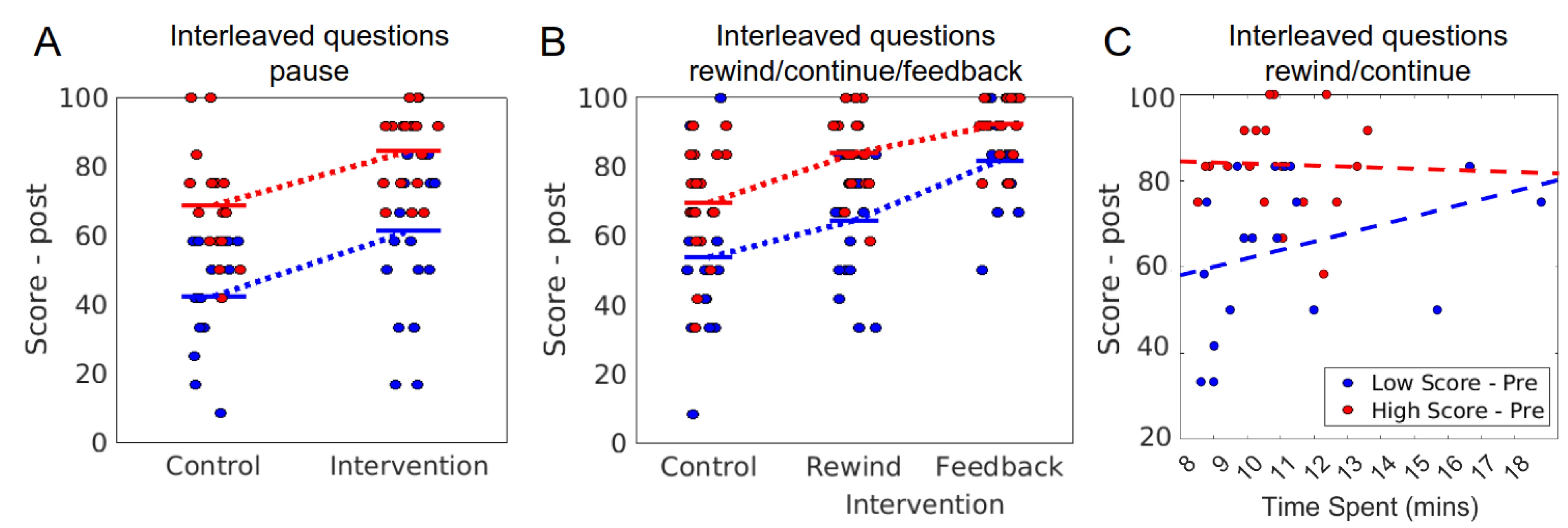
A first video is presented while assessing attention (using ISC of eye movements or EEG). This is followed by a corresponding test. This baseline is used to identify participants with high and low baseline attention (or performance). All participants are then randomized into equal parts to watch a second video either with an accompanying intervention or in a control condition (passive viewing).

Possible outcomes:



(A) Here low attending students benefit from the intervention more than attentive students in terms of test score (an interaction in the 2x2 design). The ISC metric replicates this pattern suggesting that effect is mediated by attention (B) Here all students benefit from the intervention equally, but ISC does not increase, suggesting the effect is not mediated by attention.

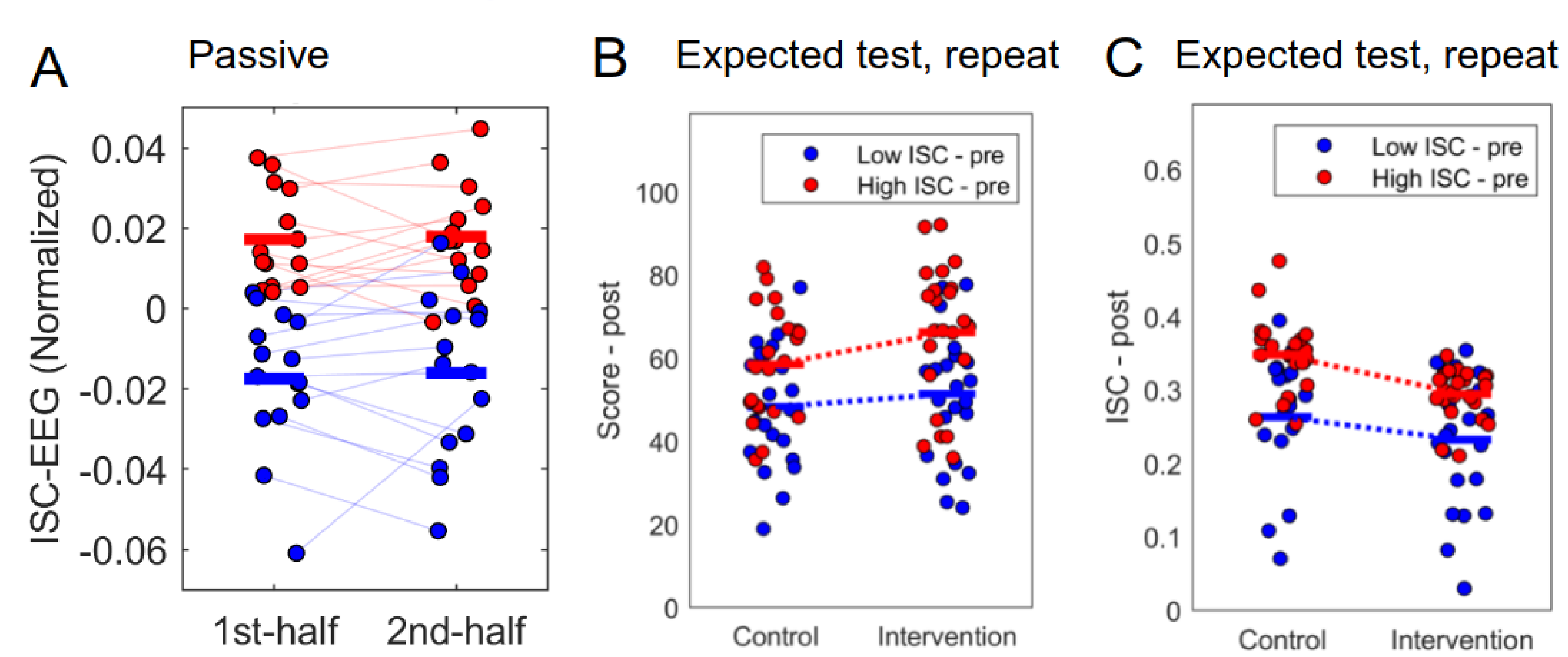
Interleaving questions in video playback improves performance, but more time only helps participants with low baseline performance.



Here we test three interventions remotely in three different RCTs (N=200 participants in total, recruited on Prolific). Low and high baseline performance groups (blue and red) are determined by a median split across participants.

(A) When questions are shown with a pause, both groups improve. In a two-way ANOVA there is a significant effect for intervention ($F(1,63) = 14.51$, $p = 0.0003$), but there is no interaction with baseline performance ($F(1,63) = 0.12$, $p = 0.73$). (B) When given the opportunity to pause, rewind or continue after a question is presented, performance increases significantly in both groups over the control condition ($F(1,69) = 9.07$, $p = 0.0037$). When in addition feedback is given on the correct responses, performance further increases ($F(1,66) = 15.88$, $p = 0.0002$) (C) In the group with high baseline performance the extra time spent with pause/rewind does not improve performance. However, in the lower performing group it does. A linear mixed effect model shows an interaction ($F=3.98$, $p=0.0005$, N=37 intervention group) confirming the differing benefits of extra study time.

Performance is higher for attentive students, but it is hard to improve attention to video.



Laboratory experiments measuring performance and attention using EEG. (A) Students (N=29) passively watch 6 short STEM videos in the lab while EEG is recorded. ISC-EEG varies significantly across students, but remains constant in time for a given student (1st and 2nd half cover 3 videos each; each dot indicates a student; color indicates high and low ISC in 1st half). (B) Students (N=92) participate in RCT. Intervention consists of repeating the video after announcing the test. Performance improves ($F(1,85)=7.23$, $p=0.008$), but there is no interaction between intervention and attention ($F(1,85)=0.51$, $p=4.76e-01$). (C) In the same experiment we measure ISC during baseline (pre). Subjects with high or low ISC during this pre-intervention video are indicated in color. ISC (attention) drops significantly ($F(1,85)=7.23$, $p=0.009$), perhaps due to fatigue or repetition of the video.

References:
Madsen et al., *PNAS*, 2021
Madsen, Parra, *PNAS* Nexus, 2022.
Cohen et al. *Neurobiology of Learning and Memory*, 2018

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