State and trait measures of attention predict performance in video-based learning

Jens Madsen* and Lucas C. Parra
Department of Biomedical Engineering, City College of New York
85 St. Nicholas Terrace, New York, NY 10031, USA

*corresponding author

Abstract

Impaired academic performance is often attributed to attentional deficits, but it remains unclear whether these reflect long-term traits or momentary fluctuations in attention. This study investigated how acute attention during engaging educational videos and trait measures of attention influenced test taking performance. Short-term retention was assessed in 152 students across four experiments using short-form educational videos. Behavioral trait measures of inattention, hyperactivity, and working memory capacity were also obtained. Acute attention, measured by EEG during video viewing, was a strong predictor of test scores. In contrast, self-reported trait measures of attention were not significant predictors. Working memory capacity and GPA positively predicted test scores. Inattention traits predicted GPA, suggesting a negative effect on overall academic performance. These results suggest that attentional traits only weakly and indirectly affect student performance. Modifying teaching methods, may help address learning deficits in inattentive students, who seem to have no problem attending to, and retaining the content of short, engaging educational videos.

Keywords: attentional engagement, attention deficit disorder, electroencephalography (EEG), working memory capacity, educational video

Introduction

Academic success is shaped by a dynamic interaction of cognitive capacities [1,2], individual personality traits [3], and educational environments [4]. Core cognitive functions such as working memory and cognitive flexibility are strong predictors of achievement [2,5,6]. Among these, attention plays a central role: students who stay focused are better able to process and retain information [7,8], whereas attentional lapses disrupt encoding and impair learning [9]. This is particularly evident in the challenges faced by students with symptoms of attention-deficit/hyperactivity disorder (ADHD), a condition known to affect approximately 5-10% of children and adolescents worldwide [10,11]. In recent years, ADHD diagnoses have risen globally, a

trend attributed to broader diagnostic criteria and increased awareness among clinicians and the public [12]. ADHD is typically characterized by inattention and hyperactivity-impulsivity, both of which are linked to poor academic outcomes, with inattention showing the strongest associations [13,14].

Extensive research has shown that individuals with ADHD, particularly when untreated, tend to perform worse on academic measures such as standardized test scores, grades, and overall school performance, even after controlling for IQ [15–17]. This suggests that ADHD impacts learning through mechanisms beyond general cognitive ability, potentially involving chronic attentional disengagement, executive dysfunction, and persistent academic difficulties. Even in undiagnosed individuals, inattention and hyperactivity scores predict school outcomes [18,19]. These findings align with growing evidence that ADHD traits are best conceptualized as dimensional rather than categorical, reflecting a continuous distribution across the population [20,21]. This dimensional perspective allows exploration of how these attentional traits impact learning in typical student samples. For the remainder, we will use Inattention and Hyperactivity as separate trait measures to assess a general participant sample.

One cognitive mechanism often implicated in these difficulties is working memory capacity (WMC), the ability to hold and manipulate information over short periods [22]. WMC has been shown to independently predict academic achievement across multiple domains, including mathematics [23] and reading [24]. Deficits in WMC contribute to difficulties with multi-step problems, especially when attentional control is required [23], and are more pronounced in those with inattention symptoms [25], persisting even when IQ and reading ability are controlled [26]. WMC is a stronger predictor of academic success than IQ in some longitudinal studies [1], and underpins higher-order functions such as reasoning, language comprehension, and problem solving [27]. WMC impairments are associated with inattentive traits, and co-occur with deficits in processing speed and verbal memory [28,29].

While attention and memory have traditionally been studied within formal educational contexts, focusing on structured instruction and classroom learning [30], students now consume media in radically different formats. Contemporary learners often engage with short-form digital content via platforms like YouTube, TikTok, and social media [31,32]. This cultural shift raises the possibility that attentional difficulties observed in academic settings may not reflect a general inability to focus, but rather a mismatch between students' habitual media experiences and the demands of conventional educational formats [33]. Moreover, frequent media multitasking, encouraged by modern digital platforms, has been associated with fragmented attention and decreased academic performance [33,34].

Short-form educational videos (typically 3-6 minutes) offer a natural test case for this question [35,36]. These formats promise to better capture students' attention by aligning with contemporary media habits, but concerns remain that they might foster shallow, surface-level engagement rather than deeper learning [37,38]. Thus, an open question emerges: can modern students sustain acute attention during brief educational videos, and do trait-level attentional measures predict engagement and learning outcomes in this setting?

Longitudinal studies link inattention to academic underperformance and self-regulation difficulties [15,39], suggesting that inattention traits primarily impairs long-term learning processes. However, recent work documents momentary attentional lapses in brief, structured tasks [40,41], raising the possibility that inattention or hyperactivity may also impact short-form learning contexts. This study tests that possibility by asking whether these traits predict reduced EEG responses and memory performance during brief instructional videos.

To address these questions, we used electroencephalography (EEG) to obtain continuous, objective measures of attentional engagement. Specifically, we analyzed intersubject correlation (ISC) of EEG signals, which quantifies neural response similarity across viewers of the same stimulus [42,43]. ISC has been shown to increase with attentional focus and to predict memory for video content [44,45].

Our first goal was to characterize how acute distraction alters the strength of neural responses, using a dual-task manipulation in which participants rewatched videos while performing mental arithmetic. Our second goal was to examine how trait-level variables, consistent of inattentive and hyperactive traits as well as, working memory capacity (WMC) relate to attentional engagement, learning outcomes and GPA. Based on prior work, we predicted that fronto-central EEG components would be most sensitive to attentional state and predictive of memory performance [44,45]. We tested whether inattentive and hyperactive traits would reduce attention and performance, or whether short-form videos remain robust to such variability [16,17]. We addressed these aims using the *BBBD* dataset (bbbd.pythonanywhere.com), comprising four experiments (N = 152) in which participants viewed short educational videos while EEG was recorded, followed by memory quizzes, inattention, hyperactivity and WMC assessments, and self-reported GPA.

Results

What effects does attention have on neural activity?

We have previously shown that neural responses to a video are similar to that of a reference group, provided the viewer is paying attention. This similarity, measured as inter-subject correlation (ISC), can be a good predictor of memory of the content of the video [44,45]. We first wanted to determine which component of the electroencephalography (EEG) is the best indicator of attentional modulation. We first analyzed two experiments from the *Brain Body Behavior Dataset* (BBBD) containing N=60 subjects (Fig. 1). Participants watched informative audiovisual narratives (3-6 minute long) from YouTube and answered associate quiz questions testing for recall and comprehension. To test the effect of attention on the neural responses, students watched the videos again in a distracted condition where they were distracted by carrying out an arithmetic task.

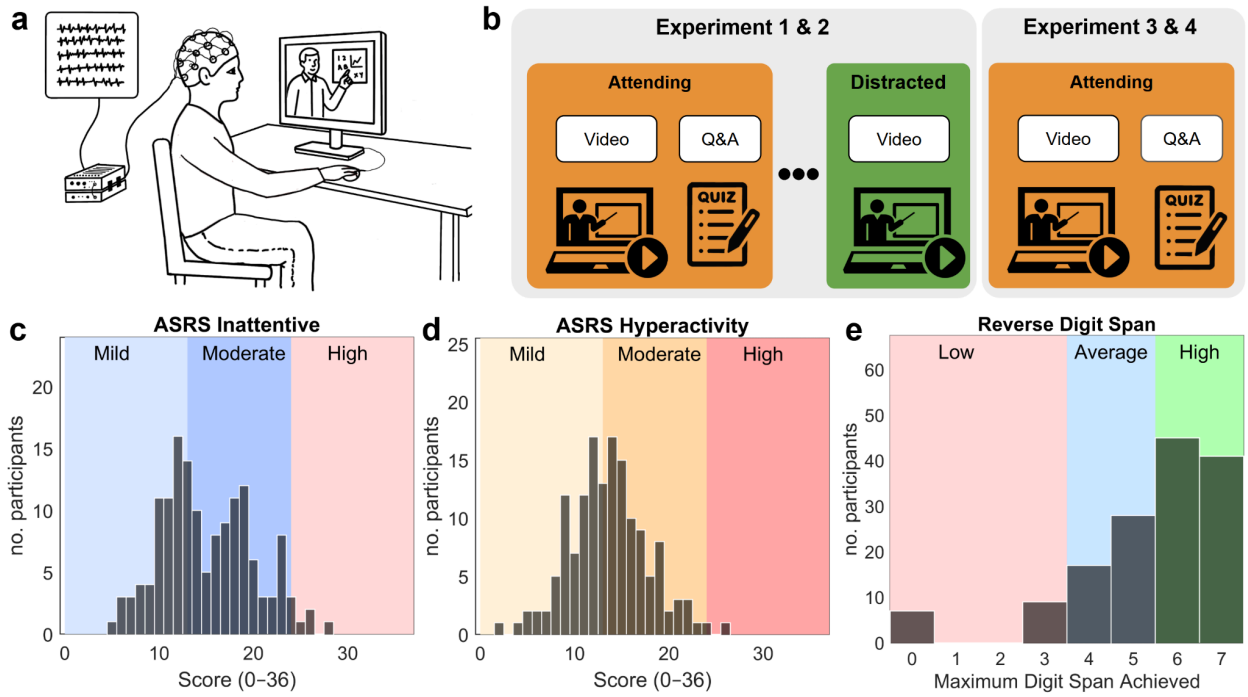

Figure 1. Experimental design and participant characteristics. a) Overview of the EEG recording setup during video-based learning tasks. **b)** In Experiments 1 (N=31) and 2 (N=29), participants watched videos under two conditions: attending, where they viewed the videos as they normally would, followed by a quiz; and distracted, where they rewatched the videos while performing a mental arithmetic task. In Experiments 3 (N=43) and 4 (N=49), participants completed only the attending condition. **(c, d)** Distributions of inattention and hyperactivity scores on the Adult ADHD Self-Report Scale (ASRS; N=149). Shaded regions in panels (c) and (d) indicate score ranges suggestive of clinically significant symptom levels, as per established guidelines [46]. **e)** Distribution of maximum reverse digit span scores (N=147), grouped into low (0–3), average (4–5), and high (6–7) working memory capacity [47].

As before, we used correlated component analysis (CorrCa [48]) to extract components that are maximally correlated between subjects. We sort them in order of ISC with the first explaining the strongest correlation between subjects. The first component had a fronto-central distribution on the scalp (Fig. 2), replicating previous results [44,49,50]. To measure the effect of attention on each component, we compute Cohen's d-prime for the difference in ISC values between the normal viewing conditions and the subsequence distracted condition (Fig. 2). We find that the first component with the strongest ISC is also most robustly reduced by the distracting task of counting.

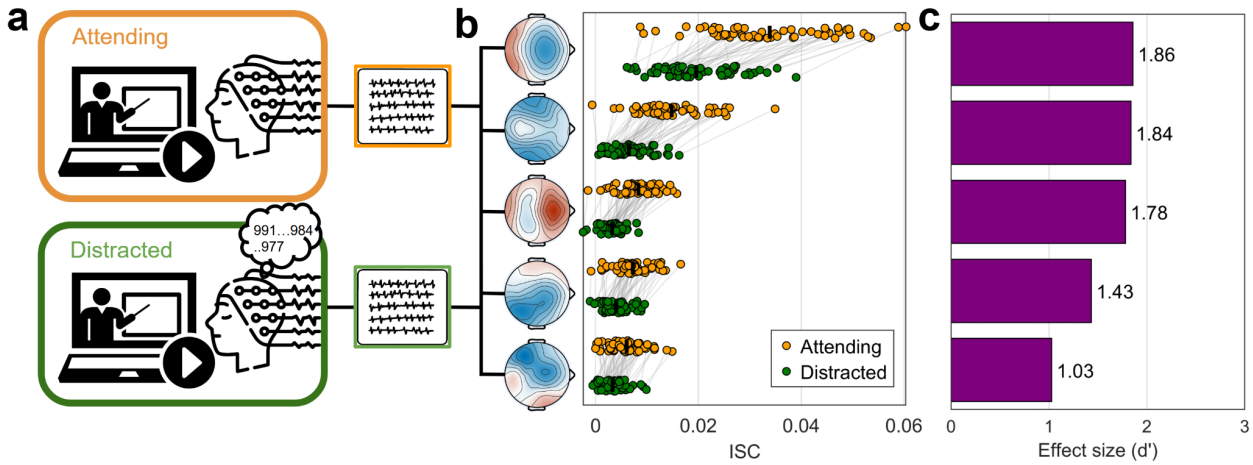

Figure 2. Effect of a distracting secondary task on video-evoked responses (mental arithmetic). a) Participants in Experiment 1 & 2 (N=60) rewatched the videos while performing a distracting mental arithmetic task (counting backwards from a random prime number between 800-1000 in steps of 7). **b)** EEG data were analyzed using correlated component analysis (CorrCA), resulting in 5 spatial filters (C1–5). We compute the ISC for each of these components in the distracted and attending conditions. Each dot is a participant and lines connect each participant's ISC values. **c)** Bar plots indicate the effect size (cohen's *d'*) on ISC. Positive d' indicates a drop in ISC in the distracted conditions. All differences were statistically significant (paired t-test, $p < 10^{-8}$, N=60, d-prime here is the $t \cdot \sqrt{N}$ [51])

Does attention or traits affect students' test scores?

Next, we analyzed the factors that predict quiz performance. The quizzes consisted of multiple choice questionnaires (10-12 questions per video) for each of the different 12 videos that were used across the four experiments from *BBBD* (N=152 participants). To capture student traits we asked them to complete a Working Memory Capacity test (reverse Digit span test). In this test the participants are shown a sequence of numbers (one-by-one) and are then asked to write the numbers in reverse order. In addition, participants filled out the Adult ADHD Self-Report Scale [52] which gives a score for *inattentiveness* and *hyperactivity*, and we also asked them to report their GPA, as a measure of overall academic performance. We used a generalized linear model to determine how attention, measured as ISC, as well as working memory capacity, GPA, inattentiveness and hyperactivity affect performance. We find that GPA and WMC are predictors of test scores ($t(109)=3.41$, $p=9 \cdot 10^{-4}$, $t(109)=3.374$, p=0.001, see Supplement S1 for complete table of statistical analysis), but inattention and hyperactivity are not ($p>0.05$) (Fig. 3a). Attention, as measured with the ISC of the first fronto-central component is a strong predictor of test score ($t(109)=4.11$, $p=7.67 \cdot 10^{-5}$).

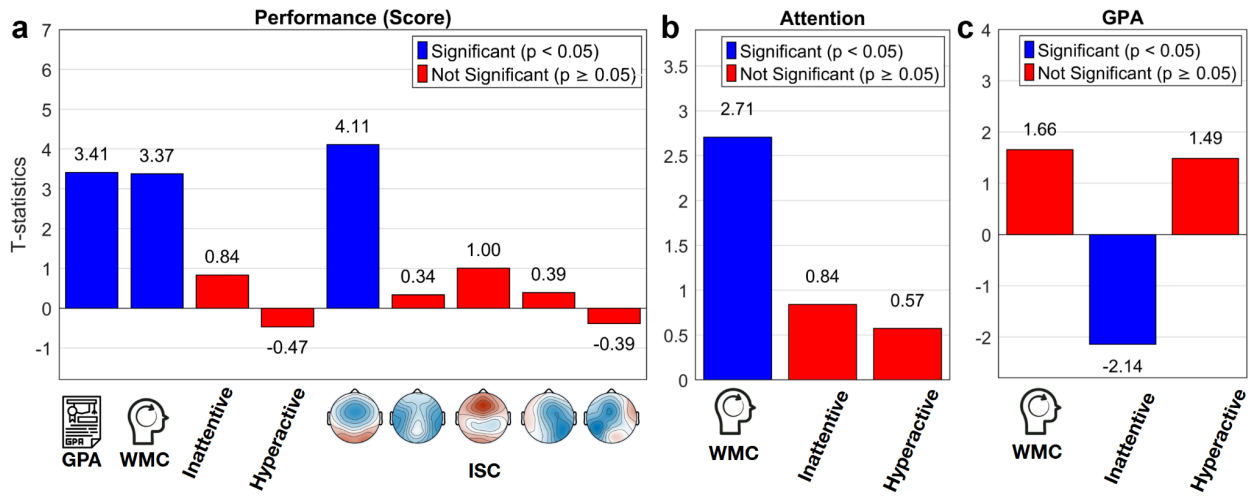

Figure 3. Factors that affect learning performance. a) t-statistics for the generalized linear model, modeling the behavioral performance of students answering questions about each short-form educational video (10-12 questions per video, N=152 participants). **b)** t-statistics for the GLM modeling the first ISC-EEG component. **c)** t-statistics for the GLM modeling GPA.

Mediation analysis of the interaction between performance, attention and traits

The previous analysis considered long-term traits, and the current state of the student, i.e. acute attentional state while watching video (ISC) and current overall academic performance (GPA). It is conceivable that the trait factors affect the current state, and thus, that they affect performance indirectly via GPA or ISC. To perform this type of mediation analysis [53] we assume, a-priori, that long-term traits affect the current state, but not vise-versa (we will discuss the basis for this and alternatives assumptions in the Discussion section). We therefore compute a model for ISC and GPA with traits as predictors (WMC, Inattention, Hyperactivity), as summarized in Fig. 4. For attention we focus on ISC of the first fronto-central component as it was most strongly modulated by attention, and was the main predictor of performance. ISC of this component was predicted by WMC with a positive effect ($t(142)=2.707$, $p=0.0076$, see Fig. 3b), but not by inattention or hyperactivity traits ($p>0.05$, the full statistical table is in the Supplement S1). GPA was predicted by inattention with a negative effect (t (115)=-2.14, $p=0.034$, see Fig. 3c) but not by WMC or hyperactivity (p>0.05, the full statistical table is in the Supplement S1).

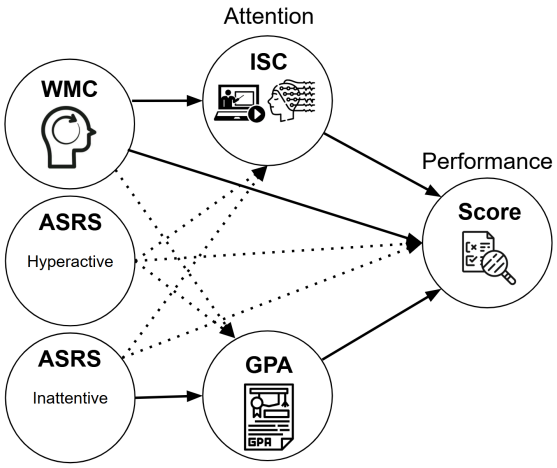

Figure 4 Summary of results: In this mediation analysis, all possible effects from left to right were tested. Solid arrows indicate statistically significant effects, dashed arrows means there was no significant effect.

Discussion

The present study investigated how acute attentional engagement and individual trait measures predict learning outcomes from short-form educational videos. Our findings demonstrate that the strongest predictor of immediate memory performance was acute attention to the video, as indexed by intersubject correlation (ISC) of EEG signals. This result aligns with foundational theories that posit attention as a *sine qua non* for effective encoding and learning [30,54]. Moreover, our neural measure of attention has previously been shown to predict quiz performance even weeks after exposure to educational material [44,55], underscoring the robustness of ISC as a marker of attentional engagement with dynamic stimuli.

Beyond acute attention, long-term measures such as working memory capacity (WMC) and GPA emerged as significant predictors of performance. This finding is consistent with extensive literature demonstrating that WMC underpins academic achievement across diverse domains, including mathematics and reading comprehension [2,23,24]. WMC facilitates the maintenance and manipulation of information during learning tasks [22], and our results suggest it also supports moment-to-moment attentional engagement with educational stimuli. Higher GPA, a proxy for overall academic success, likely reflects accumulated cognitive skills and prior knowledge that aid in encoding new information, consistent with theories of educational attainment [1].

In contrast, self-reported inattentiveness, while a predictor of lower GPA, did not significantly predict neural attention or immediate memory performance. This finding supports the view that ADHD traits, particularly inattention, impact cumulative academic outcomes through chronic disengagement [16,17], rather than through acute deficits in attentional engagement with short, structured materials. Notably, neither inattentiveness nor hyperactivity significantly impaired attention to or learning from short

videos, suggesting that modern short-form educational content can successfully engage students across a range of attentional profiles.

Our EEG results further corroborate prior work demonstrating that attentional modulation during naturalistic narrative engagement is predominantly reflected in fronto-central neural components [43,49]. Here we find that it is this EEG component that best predicts learning performance. The anterior-central topography observed is consistent with large-scale attentional control networks implicated in cognitive neuroscience [56,57], supporting the interpretation that fronto-central cortical areas are engaged during active processing of educational content.

This conclusion is also consistent with the positive effect we found of WMC onto ISC. This analysis was motivated by the fact that WMC reflects a general cognitive skill of an individual. But of course, WMC could be aided by an ability to maintain attention, and an ability to retrain content in working memory may help maintain attention. So these two factors likely interact, and we could have changed the direction of our analysis without affecting any of the other results.

Our study also provides broader insight into contemporary educational environments. As students increasingly consume fast-paced digital content, short-form educational videos appear well-suited to engage attention even among individuals with attentional trait deficits. This suggests that concerns about a "crisis of attention" in younger generations [31,32] should be nuanced: when content matches habitual media consumption patterns, acute attentional engagement remains normal. However, we caution that while acute attention predicts immediate memory performance, it does not necessarily guarantee deeper semantic learning or long-term consolidation into broader knowledge networks, as emphasized in the levels-of-processing framework [58]. Capturing attention is necessary but insufficient for durable learning and comprehension. Future educational strategies should not only harness the engagement potential of short-form media but also incorporate scaffolds that promote elaborative, semantic processing, encouraging integration of new material into existing cognitive frameworks [59].

In conclusion, our results highlight the critical role of acute attentional engagement in video-based learning and suggest that trait-level inattentiveness may not necessarily impede learning when materials are brief, structured, and engaging. As education continues to evolve in an increasingly digital landscape, understanding the interaction between neural attention, cognitive traits, and media formats will be essential for designing effective, inclusive educational strategies.

Limitation of the study

Several limitations should be noted. First, our study focused on immediate retention after video viewing; it remains unknown whether acute attentional engagement predicts long-term knowledge retention or transfer to novel contexts. Second, our findings are based on brief interventions and may not generalize to more extended or cumulative learning scenarios. Future research should address these questions through longitudinal designs and by exploring interventions that foster deeper processing during video-based learning. Third, the analysis of GPA was based on self-reports and only applicable to college

students that had a GPA. Indeed, several participants (42 out of 152) did not report GPA which may have been a bias against reporting low scores, or they may not have had a GPA as they did not attend college. So generally, the GPA analysis should be interpreted with caution.

Methods

Participants

A total of 152 participants from four experiments (Experiments 2-5 of the Brain, Body, Behavior Dataset [BBBD]) were included in this study. All participants watched short, informative audiovisual narratives while EEG was recorded, along with other physiological and behavioral measures depending on the experiment. Participants provided informed consent under protocols approved by the relevant ethics committees. In Experiment 2, 31 participants were included (21 female; age range = 18-50 years, M = 25.79, SD = 8.13). In Experiment 3, 29 participants were included after removing 3 due to poor data quality (21 female; age range = 18-57 years, M = 25.93, SD = 8.94). In Experiment 4, 43 participants were included after removing 3 (24 female; age range = 18-45 years, M = 25.09, SD = 6.49). In Experiment 5, 48 participants were included after removing 2 (26 female; age range = 18-49 years, M = 25.71, SD = 7.98). In total, 152 participants (92 female) aged 18-57 years (M = 25.65, SD = 7.90) were analyzed across the four experiments. Demographic and modality information is detailed in the BBBD dataset documentation.

Stimuli

Across the 4 experiments participants watched a subset of 11 unique informative audiovisual narratives selected from popular YouTube channels known for short explanatory content, including minutephysics, Kurzgesagt - In a Nutshell, MinuteEarth, What If, Be Smart, Khan Academy, and eHowEducation. These videos cover topics in physics, biology, astronomy, and computer science and have been used in prior studies investigating attention and learning from video-based instruction. In Experiment 2, participants viewed five videos from minutephysics, Kurzgesagt, and MinuteEarth, covering topics in physics, biology, and computer science. Video durations ranged from 2:23 to 7:49 minutes (M = 4.94 min). In Experiment 3, six videos were shown, sourced from Khan Academy, eHowEducation, What If, and Be Smart. Topics included biology, physics, and astronomy, with durations ranging from 3:12 to 6:27 minutes (M = 5.16 min). In Experiment 4, six videos overlapped with prior experiments, including content from minutephysics, Kurzgesagt, What If, Be Smart, and eHowEducation, covering physics and biology topics (range: 3:12-7:49 minutes). In Experiment 5, participants viewed four videos from minutephysics, Kurzgesagt, and Be Smart, with durations between 3:29 and 7:49 minutes (M = 5.88 min).
All videos were audiovisual narratives that presented core scientific or conceptual explanations in a visually engaging style. The full list of videos, their durations, source channels, and YouTube IDs are documented in the BBBD dataset paper.

Procedure

All experiments were conducted at the City College of New York in a sound-attenuated booth with controlled ambient lighting. The study protocol was approved by the Institutional Review Boards (IRB) of the City University of New York, and documented informed consent was obtained from all participants. Participants were seated approximately 60 cm from a 27" monitor, and videos were presented with audio played through stereo speakers positioned at 60° angles on either side of the screen. EEG and EOG signals were recorded throughout the experiments using a BioSemi ActiveTwo system. Additional physiological and behavioral signals (e.g., ECG, gaze, pupil diameter, head position, respiration) were also collected and are available in the full BBBD dataset, but are not analyzed in the current study.

In all experiments, participants watched informative audiovisual narratives under an attentive condition, in which they were instructed to view the videos as they normally would at home while remaining relaxed and still. After each video (or set of videos), participants completed a multiple-choice quiz (10-12 items per video) testing factual memory of the content. The order of videos and questions was randomized across participants to control for order effects.

In Experiments 1, 2, and 4 (corresponding to BBBD Experiments 2, 3, and 5), participants also viewed the same videos under a distracted condition, where they were asked to silently count backwards in decrements of 7 from a randomly selected prime number between 800 and 1,000. This condition was designed to suppress attention using a mental arithmetic task.

The segmentation of physiological recordings was aligned precisely across participants using embedded audiovisual markers (a flash and beep) placed at the beginning and end of each video, detected via a StimTracker (Cedrus).

Preprocessing of EEG

The EEG was recorded using a BioSemi Active Two system at a sampling frequency of 2048 Hz. Participants were fitted with a standard, 64-electrode cap following the international 10/10 system. In addition the electrooculogram (EOG) was recorded with six auxiliary electrodes (one located dorsally, ventrally, and laterally to each eye).

The EEG and EOG data was first filtered with an analog band-pass filter between 0.016 and 250 Hz by the Active two system. The signal was then digitally high-pass filtered (0.5 Hz cutoff) and notch filtered at 60 Hz (line noise). To remove artifacts and outliers Robust PCA was used, and subsequently the signal was low-pass filtered (64 Hz cutoff) and down-sampled to 128 Hz. Bad electrode channels were identified manually and replaced with interpolated channels. The interpolation was performed using the 3D cartesian coordinates from the electrode cap projected onto a plane. An interpolation method was used to recreate each channel, derived from all surrounding "good" electrodes. The EOG channels were used to remove eye-movement artifacts by linearly regressing them from the EEG channels, i.e. least-squares noise cancellation.

In each EEG channel, outlier samples were identified (values exceeding 4 times the distance between the 25th and the 75th quartile of the median-centered signal) and samples 40 ms before and after such outliers were replaced with interpolated samples.

Intersubject correlation and attention analysis of EEG

For the neural signals recorded using EEG the Inter-subject correlation was computed using correlated component analysis [48]. This method finds a model that linearly combines electrodes that capture evoked activity most correlated between subjects. The model consists of several projection vectors that linearly combine electrodes, on which the data is projected (components), capturing independent sources of correlation between subjects. The ISC of each component is obtained by computing the correlation coefficients of the projected EEG time-course between each participant and all other participants. In order to compare ISC values across the 4 different experiments, spatial filters were estimated on Experiment 3 and applied to all other experiments.

For the analysis of on attentional modulation of ISC, we computed the model combining data from Experiments 1 and 2 including the attending and distracted conditions. For the analysis of quiz performance and mediation, we computed the components with the attentive conditions of experiment 2, and used this model to measure ISC in the attentive conditions for all 4 experiments.

Reverse Digit Span Task

Participants completed a reverse digit span task in which they were asked to repeat sequences of digits in reverse order. Sequence lengths ranged from 3 to 7 digits, with two trials per length, yielding a total of 10 trials. Each response was scored as correct if all digits were recalled in the correct reversed order. To quantify performance, we computed a maximum span score, defined as the highest sequence length at which the participant correctly recalled at least one trial. This scoring approach is consistent with standard procedures used in neuropsychological assessments, where maximum span length reflects working memory capacity [47].

Statistical analysis

We used generalized linear mixed effect models following the hypothesized causal effects shown in Fig. 4 with all arrows considered in the models pointing from left to right. In abbreviated Wilkson notation used by the matlab function fitglme() the models read as follows:

To model the factors affecting quiz performance, i.e. number of correct responses:

$\text{logit(Score)} \sim 1 + \text{GPA} + \text{WMC}_{\text{DigitSpan}} + \text{ASRS}_{\text{Inattentive}} + \text{ASRS}_{\text{Hyperactive}} + \text{ISC}_{\text{eeg-1}} + \text{ISC}_{\text{eeg-2}} + \text{ISC}_{\text{eeg-3}} + \text{ISC}_{\text{eeg-4}} + \text{ISC}_{\text{eeg-5}} + (1|\text{Exp})$

Distribution = Binomial

To model factors affecting ISC for the first component of the EEG:

$\text{ISC}_{\text{eeg-1}} \sim 1 + \text{WMC}_{\text{DigitSpan}} + \text{ASRS}_{\text{Inattentive}} + \text{ASRS}_{\text{Hyperactive}} + (1|\text{Exp})$

Distribution = Normal

To model the factors affecting GPA:

$\text{logit}(\text{GPA}_{\text{norm}}) \sim 1 + \text{WMC}_{\text{DigitSpan}} + \text{ASRS}_{\text{Inattentive}} + \text{ASRS}_{\text{Hyperactive}} + (1|\text{Exp})$

Distribution = Normal

Because quizzes, videos and sample populations differed across experiments we included Exp as a categorical random effect variable in all models. All other factors were fixed effect graded variables. GPA was self-reported and only applicable for current or former college students (123 of 152). For students where it was missing (13 out of 123) we imputed the median GPA across students. The model for correct responses assumes a Binomial distribution and the fit is given the possible maximum correct responses which differs across quizzes. To allow the use of the logistic link function, GPA was normalized to 0-1, with values exceeding 1 clipped (a few participants reported GPA above 4).

Resource availability

Lead Contact

Jens Madsen, jmadsen@ccny.cuny.edu

Data and code availability

The code to reproduce each figure is available on osf.io/u72k3. The data used for the experiment is publically available at *BBBD* website bbbd.pythonanywhere.com. The spatial filters used in the analysis are shared on OSF as well.

Author Contributions

J.M. and L.C.P. contributed to the conception and design of the study. J.M. contributed to the acquisition of data. J.M. contributed to the analysis of data. J.M. and L.C.P. contributed to the statistical analysis of the data. J.M. and L.C.P. contributed to the writing of the manuscript and/or the figures.

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Declaration of interests

The authors declare no competing interests.

Declaration of generative AI and AI-assisted technologies

During the preparation of this work, the author(s) used ChatGPT in order to correct language, grammar and spell check. After using this tool or service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Supplemental information

Section S1 - Generalized linear model output

Factors affecting performance (score):

Generalized linear mixed-effects model fit by PL

Model information:

Number of observations	119
Fixed effects coefficients	10
Random effects coefficients	4
Covariance parameters	1
Distribution	Binomial
Link	Logit
FitMethod	MPL

Formula:

Score ~ 1 + GPA + WMC + Inattentive + Hyperactive + ISC_eeg_1 + ISC_eeg_2 + ISC_eeg_3 + ISC_eeg_4 + ISC_eeg_5 + (1 | Exp)

Model fit statistics:

AIC	BIC	LogLikelihood	Deviance
226.93	257.5	-102.47	204.93

Fixed effects coefficients (95% CIs):

Name	stimate	SE	tStat	DF	pValue	Lower	Upper
{'(Intercept)'}	-1.8019	0.32212	-5.5939	109	1.6666e-07	-2.4404	-1.1635
{'GPA' }	0.20405	0.059833	3.4103	109	0.00091106	0.085458	0.32263
{'WMC' }	0.067786	0.02009	3.374	109	0.0010267	0.027967	0.1076
{'Inattentive'}	0.0055089	0.0065858	0.83649	109	0.40471	-0.0075439	0.018562
{'Hyperactive'}	-0.0036947	0.007807	-0.47325	109	0.63698	-0.019168	0.011779
{'ISC_eeg_1' }	19.474	4.7377	4.1105	109	7.6748e-05	10.084	28.864
{'ISC_eeg_2' }	2.3485	6.9659	0.33714	109	0.73666	-11.458	16.155
{'ISC_eeg_3' }	11.688	11.633	1.0047	109	0.31728	-11.369	34.745
{'ISC_eeg_4' }	5.1097	13.017	0.39254	109	0.69542	-20.689	30.909
{'ISC_eeg_5' }	-4.8603	12.542	-0.38753	109	0.69912	-29.718	19.997

Random effects covariance parameters:

Group: Exp (4 Levels)

Name1	Name2	Type	Estimate
{'(Intercept)'}	{'(Intercept)'}	{'std'}	0.31245

Group: Error

Name	Estimate
{'sqrt(Dispersion)'}	1

Factors affecting ISC:

Generalized linear mixed-effects model fit by PL

Model information:

Number of observations	146
Fixed effects coefficients	4
Random effects coefficients	4
Covariance parameters	2
Distribution	Normal
Link	Identity
FitMethod	MPL

Formula:

ISC_eeg_1 ~ 1 + WMC + Inattentive + Hyperactive + (1 | Exp)

Model fit statistics:

AIC	BIC	LogLikelihood	Deviance
-932.31	-914.41	472.16	-944.31

Fixed effects coefficients (95% CIs):

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
{'(Intercept)'}	0.022575	0.0046203	4.8861	142	2.7404e-06	0.013442	0.031709
{'WMC' }	0.0012598	0.00046546	2.7067	142	0.0076302	0.00033971	0.00218
{'Inattentive'}	0.00014268	0.00016949	0.84185	142	0.40129	-0.00019236	0.00047773
{'Hyperactive'}	0.00011285	0.00019709	0.5726	142	0.56782	-0.00027675	0.00050246

Random effects covariance parameters:

Group: Exp (4 Levels)

Name1	Name2	Type	Estimate
{'(Intercept)'}	{'(Intercept)'}	{'std'}	0.0052881

Group: Error

Name	Estimate
{'sqrt(Dispersion)'}	0.0092081

Factors affecting GPA

Generalized linear mixed-effects model fit by PL

Model information:

Number of observations	119
Fixed effects coefficients	4

Random effects coefficients	4
Covariance parameters	2
Distribution	Normal
Link	Logit
FitMethod	MPL

Formula:

GPAnorm ~ 1 + WMC + Inattentive + Hyperactive + (1 | Exp)

Model fit statistics:

AIC	BIC	LogLikelihood	Deviance
316.2	332.87	-152.1	304.2

Fixed effects coefficients (95% CIs):

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
{'(Intercept)'}	1.291400	0.44894	2.8764	115	0.0047948	0.40208	2.1806
{'WMC' }	0.083428	0.050399	1.6553	115	0.10058	-0.016404	0.18326
{'Inattentive'}	-0.034875	0.0163	-2.1396	115	0.034498	-0.067162	-0.0025888
{'Hyperactive'}	0.031835	0.021437	1.485	115	0.14027	-0.010628	0.074298

Random effects covariance parameters:

Group: Exp (4 Levels)

Name1	Name2	Type	Estimate
{'(Intercept)'}	{'(Intercept)'}	{'std'}	0.23505

Group: Error

Name	Estimate
{'sqrt(Dispersion)'}	0.11232