The Brain Rot Effect: The case for adaptive attentional bandwidth

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Abstract

Short-form "brain rot" content on platforms like TikTok is widely viewed as harmful for attention and learning. We find that brain rot can benefit learners with higher stimulation needs. We eyetracked young adults (N = 75) while they watched physics videos presented alone or alongside a task-irrelevant "brain rot-style" animated video. Individuals who reported preferring brain rot learned better from the brain rot condition than from the blander control condition. Furthermore, eye blinks and pupil dilation suggest that those who prefer brain rot were less overstimulated by brain rot content and required more effortful executive control to sustain attention to control content. Finally, preference for brain rot in our task is associated with higher media consumption and tolerance for high stimulation. These findings may point to individual variation in optimal cognitive load and provide preliminary support for an adaptive account of attentional bandwidth.

Keywords: brain rot; digital media; adaptive attention; cognitive load; learning; metacognition; eye-tracking

Introduction

Trends in digital media favor fast paced, visually stimulating features to capture attention (Cutting, 2016; Simon et al., 1971). The emergent attention economy has given rise to extreme formats like "brain rot", where two unrelated videos are presented simultaneously. Although brain rot content might sound as though it should introduce distraction into learning, its popularity might suggest otherwise. We use brain rot to test whether attention adapts to increased perceptual load.

Features of brain rot are viewed as harmful

Both popular discourse and academic research link short-form and high-stimulation media trends to shorter attention spans, digital addiction, diminished critical thinking, and attentional disorders (Christakis et al., 2018; Hayes, 2025; Lissak, 2018; Nguyen et al., 2025; Ward et al., 2017; Wu, 2016). Leading theories suggest the heightened audiovisual stimulation disrupts processing and learning (Christakis et al., 2012; Lillard & Peterson, 2011; Nguyen et al., 2025; Shepherd & Kidd, 2024).

Then why is brain rot popular?

Brain rot was the Oxford Word of the Year in 2024, and refers to simultaneous video streams designed to capture and hold attention on social media platforms like Instagram and TikTok (Heaton, 2024). Brain rot can also refer to the assumed cognitive decline due to overconsumption of this type of content (Yousef et al., 2025). Here, we operationalize brain rot as two videos presented simultaneously via split screen, with a primary video alongside a second visually engaging but irrelevant video.

The recent appearance of study tools that convert students' notes into brain rot suggests that at least some people believe this content facilitates learning (Upton-Clark, 2024). Brain rot could theoretically improve processing for individuals who need greater stimulation for optimal learning, in line with work on learning from accelerated playback speeds (Chen et al., 2024; Lang et al., 2020; Tharumalingam et al., 2025). We test the idea that brain rot may not uniformly impair processing and downstream learning for all learners, and could instead provide greater stimulation for learners who need more, thus facilitating their learning.

Distinct sources of cognitive load

Human attention is limited; thus, the system must allocate resources to support effective perception, processing, and learning with respect to resource limitations. Cognitive load refers to the demands that a task places on these limited resources. The specific features of a task impact cognitive load. Perceptual complexity—like a busy visual scene—increases the need to focus on task-relevant information and ignore task-irrelevant distractors. On the other hand, executive control requires resources to stay on task and hold relevant information in working memory, among other executive functions (Kahneman, 1973; Reese et al., 2016; Sweller et al., 1998). Current models of processing distinguish between perceptual load and executive load.

The load theory of attention provides a framework that accounts for the distinct effects of perceptual and executive load on task performance (Lavie et al., 2004). Task performance may improve under higher perceptual load, counter to traditional accounts of cognitive load. These findings are explained by a two-stage account. Under high perceptual load, an early perceptual mechanism filters out distractors before they are processed. Under low perceptual load, distractors are processed and must be suppressed by a late-stage executive control mechanism. As a result, high perceptual load reduces distractor interference, while high executive control load increases interference, a pattern widely supported by both

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theoretical and empirical work (Lavie, 2005, 2010).

These differential effects demonstrate that processing is not only sensitive to the degree of cognitive load, but also to the source of load. In this view, people may seek higher perceptual load (like brain rot) to maintain a balance between perceptual and executive load. Variation in preferences for highly stimulating media, as well as mixed findings in the playback-speed literature, may be explained by variation in this optimal range of stimulation.

Brain rot as an adaptive attentional strategy

Here, we investigate brain rot as a potential case study of how attentional capacity may be adaptive rather than fixed. Individuals may vary in the range of perceptual stimulation that optimally supports engagement and processing. Too much overstimulates and impairs processing, resulting in reduced performance, while too little under-stimulates and requires greater executive effort, also reducing performance. If true, this would predict that high perceptual load would not uniformly impair learning. Rather, the impact would depend on the (mis)match between the properties of the stimulus and the individual's optimal range of stimulation.

We test this account by manipulating perceptual load with brain rot stimuli during a learning task. We find that the same material disrupts processing for some participants while improving processing for others, and that the effect is predicted by their post-test preference for brain rot. Exploratory eye-tracking analyses further support an adaptive attentional bandwidth framework by differentiating perceptual and executive load.

Methods

Participants

We recruited seventy-five undergraduate psychology students (M_{age} = 20.8, SD = 2.7, range = 18-35) from a university subject pool. We excluded fourteen additional participants due to technical issues (n = 9), excessive environmental noise (n = 4), or experimenter error (n = 1). We compensated participants with course credit and a $5 bonus.

Stimuli

Primary stimuli were two excerpts of educational physics videos lasting 2 minutes and 15 seconds.[1] The physics videos were presented on the bottom half of a split-screen visual display (see Figure 1). The top half consisted of either a static gray background or an unrelated, visually engaging gameplay video[2], according to a counterbalanced, within-subject trial condition (control vs. brain rot). We paired each video with a 30-item multiple-choice test assessing learning of the physics material.

[1] Adapted from 'Windmills Are NOT Like Dams' and 'How Modern Light Bulbs Work' by @minutephysics on YouTube.

[2] Adapted from Subway Surfers Gameplay [4K 16x9] No Copyright by @subwaysurfers on YouTube.

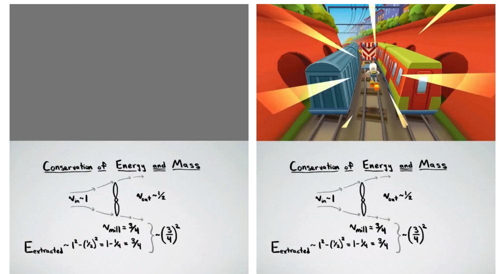

Figure 1: Screenshots of matched videos for control condition (left) and brain rot condition (right).

Procedure

Participants completed the study in a quiet, darkened room to control for distractions. We presented the visual stimuli on a monitor connected to a desktop-mounted EyeLink 1000 eye tracker (SR Research Ltd. 2005). The EyeLink monocularly recorded gaze location and pupil diameter at 1000Hz. We positioned participants 70 cm from the display. We calibrated the eye tracker using a standard nine-point calibration procedure followed by an identical validation sequence before each trial. We repeated the validation sequences until satisfactory, < 0.5 degrees of average error.

Participants watched a video and completed a corresponding multiple-choice test in each of two within-subject blocks. Participants were required to view each video in its entirety at least once, but were allowed to re-watch the video continuously until they felt ready to complete the test. After the initial viewing, the video looped automatically until participants looked away from the screen for more than one second. Following each video, participants completed a 30-item test assessing learning of the video content. Following both blocks, participants gave their preferences for the two video presentations and answered questions about their media consumption habits. We counterbalanced video content across participants and randomized trial condition across trials.

Brain rot preference score

We created a composite score of brain rot preference from five equally weighted, binary questions. We asked participants which of the two videos they found more engaging, more enjoyable, more effective for learning, easier for sustaining their attention, and more preferred overall. Higher composite scores indicate a stronger preference for the brain rot video presentation over the control presentation.

Media habit score

We created a media habit score to quantify participants' prior consumption of online media. This composite score was composed of 9 range-normalized and equally weighted questions, including 1 binary and 8 ordinal items. These items asked participants about their screen time, time spent watching short-form content, frequency of watching sped-up content, frequency of watching brain rot content, frequency of consuming multiple streams of content simultaneously, frequency of consuming unrelated media while working or studying, attitude toward engagement with brain rot content, experience using brain rot study tools, and interest in using brain rot study tools. Higher composite scores correspond to heavier online media consumption, stronger proclivities for highly stimulating content, and stronger interest in educational applications of brain rot.

Eye-tracking data pre-processing

Pupil dilation We used pupil size as a proxy measurement of executive load. To quantify pupil size, we removed 150ms before and after a blink event to account for blink-induced pupillary response (Bentivoglio et al., 1997). We then normalized pupil size for each participant using the first 10 seconds of the current trial to account for different individual baselines for each trial type (brain rot and control). Finally, we scaled pupil change from baseline for clearer interpretation.

Eye blink behavior Endogenous eye blink behavior reflects the regulation of sensory and information processing (for review see Callara et al., 2023; Stern et al., 1984). We analyzed blink behavior to test the effect of increased perceptual load in the brain rot condition as a function of participants' preference scores using two metrics: total blink time and blink count.

Total blink time is the total number of eye-tracking samples occurring during a blink event. Since blink event samples and missing data cannot easily be differentiated, all blink events longer than one second were removed, a standard threshold for identifying endogenous eye blinks (Stern et al., 1984). Participants used a chin rest, so any blink events longer than one-second are likely due to drowsiness rather than missing data. This data filtering resulted in the removal of 0.6% of all data. The final blink sample count was summed and divided by remaining samples. The final measure is total blink time per sample for a given trial. Blink count was also quantified as distinct blink events. Both total blink time and blink count were log-transformed prior to analysis to meet model assumptions (Bentivoglio et al., 1997).

Results

Brain rot has heterogeneous effects on learning and metacognition

We assessed whether the simultaneous, brain rot-style presentation of unrelated video game content during viewing of physics videos affected performance on a subsequent test. We ran a generalized linear mixed-effects model predicting trial-level accuracy, with condition (control vs. brain rot) and condition order as fixed effects and by-participant random intercepts and condition slopes. This model revealed a significant effect of condition order ($\beta = 0.29$, $t = 3.35$, $p < .001$) such that performance was better in the second within-subjects condition. There was no significant effect of condition ($\beta = -0.14$, $t = -1.56$, $p = .12$). There was no group-level effect of brain rot on test performance. However, this null effect on the group-level obscured substantial heterogeneity in the effect of brain rot across participants. Consistent with this variation, the mean absolute difference in by-participant average accuracy between conditions was 15.5% (SD = 0.12, range = 0-0.5). Our sample was evenly split between participants who learned better in the control condition (49.3%) vs. the brain rot condition (45.3%).

We also tested for condition differences in participants' metacognitive sensitivity, or the relationship between certainty and accuracy. We quantified metacognitive sensitivity using the pROC package in R to calculate the area under the Type 2 ROC curve, or AUC2. This curve captures the hit rate vs. false alarm rate for whether higher trial-level certainty predicts accuracy. An area of 0.5 corresponds to at-chance performance, and higher AUC2 values indicate stronger metacognitive sensitivity.

A linear mixed-effects model predicting AUC2, with condition (control vs. brain rot) and condition order as fixed effects and random intercepts per participant, revealed no significant effect of condition ($\beta = 0.03$, $t = 1.22$, $p = .23$) or of condition order ($\beta = 0.03$, $t = 1.50$, $p = .14$). The null effect of condition reflects bidirectional effects on the individual level. The mean by-participant difference in AUC2 between conditions was 15.1% (SD = 0.13, range = 0.003-0.6). Our sample was again evenly split between participants who had higher metacognitive sensitivity in the control condition (49.3%) vs. the brain rot condition (49.3%). For most participants (65.3%), the condition they learned better in was also the condition in which they showed better metacognitive sensitivity.

Brain rot preferers learn better from brain rot, worse from traditional content

We used participants' reported preferences for the brain rot-style video presentation or the control presentation to test whether participants were aware of which condition was more conducive to their learning. Brain rot preference scores were right-skewed (M = 1.49 out of 5, SD = 1.79). Nearly half (n = 35, or 46.7%) of the participants had a score of zero, meaning that they preferred the control presentation across all five questionnaire items. Eight (or 10.7%) participants had a brain rot preference score of 5, reflecting a universal preference for the brain rot presentation. Those who learned better in the brain rot condition had higher brain rot preference scores (M = 2.03) than those who learned better in the control condition (M = 0.68), indicating that subjective preference was calibrated to learning outcomes.

We assessed whether participants' post-test content preferences predicted different learning outcomes, and found a crossover effect (see Figure 2A). Participants with a stronger brain rot preference performed better in the brain rot condition, whereas participants with a weaker brain rot preference performed better in the control condition. We fit a linear mixed-effects model predicting participants' average accuracy, with condition (control vs. brain rot), scaled brain rot preference

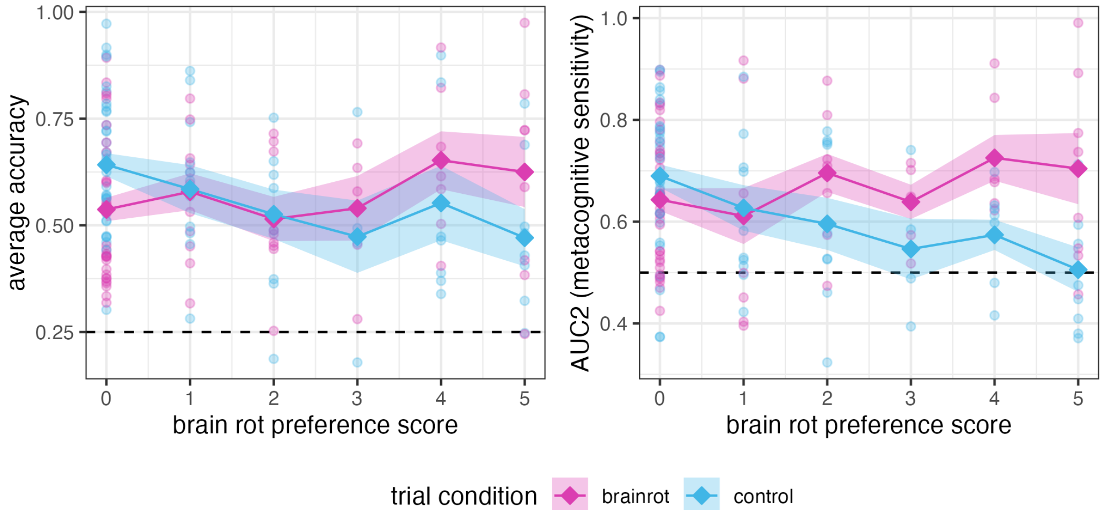

Figure 2: Preference for brain rot predicts differential test performance (left) and metacognitive sensitivity (right) across conditions. Dashed lines represent at-chance performance (left) and metacognition (right). Points are participant averages by condition and are jittered vertically. Diamonds are condition means by preference score. Ribbons represent SE.

score, and condition order as fixed effects and random intercepts per participant. This model revealed a significant effect of condition order (β = 0.04, t = 2.08, p = .04), a significant effect of scaled brain rot preference score (β = -0.05, t = 2.55, p = .01), and a significant interaction between condition and scaled brain rot preference score (β = 0.08, t = 3.59, p < .001). The effect of the brain rot condition was not significant (β = -0.02, t = -1.22, p = .22). Higher brain rot preference scores predicted lower test performance in the control condition, but higher test performance in the brain rot condition.

Brain rot preferers have poor metacognition for traditional content

Stronger brain rot preference predicted worse metacognitive sensitivity in the control condition and better metacognitive sensitivity in the brain rot condition (see Figure 2B). We fit a linear mixed-effects model predicting AUC2, with condition (control vs. brain rot), scaled brain rot preference score, scaled average accuracy, and condition order as fixed effects and random intercepts per participant. The model revealed a significant effect of brain rot preference score (β = -0.04, t = -3.02, p = .003), a significant effect of scaled average accuracy (β = 0.06, t = 6.42, p < .001), and a significant interaction between condition and brain rot preference score (β = 0.06, t = 2.97, p = .004). Better task performance was associated with higher AUC2 scores, as is common with many measures of metacognition (Rahnev, 2025). Critically, the interaction between condition and brain rot preference remained after controlling for task performance. Higher brain rot preference was associated with enhanced metacognition in the brain rot condition, but diminished metacognition when learning from the less stimulating control presentation.

Brain rot preference is not captured by gaze patterns

Looking behavior was analyzed within the brain rot condition alone since looking to the video was at ceiling during the control condition. A linear regression predicting the proportion of time spent looking to the content video during brain rot trials (as opposed to the brain rot video) revealed no effect of brain rot preference score (β = -0.02, t = -1.16, p = 0.25) or condition order (β = 0.03, t = 0.85, p = 0.4). A linear regression predicting the number of switches made between the brain rot and content videos similarly showed no significant effect of brain rot preference score (β = 6.4, t = 1.16, p = 0.25) or condition order (β = -19.24, t = -1.7, p = 0.09). These results indicate that preference for brain rot does not predict differences in looking behavior in our task.

Lastly, the duration of watching did not differ by condition or preference. A linear mixed-effects model predicting total viewing time confirmed no effects of condition (β = .018, t = 0.12, p = 0.9), brain rot preference score (β = 0.07, t = 0.58, p = 0.57), or condition order (β = -0.2, t = -1.26, p = 0.21), and no interaction between trial condition and brain rot preference score (β = 0.05, t = 0.37, p = 0.71). Since preference does not predict watching duration in the brain rot condition (M = 2.46, SD = 1.08) or the control condition (M = 2.51, SD = 1.1) we restrict our analysis of eye blink and pupil dilation to the first loop of each video.

Eye blink behavior supports variation in experience of perceptual load

A linear mixed-effects model predicting the total blink time (log-transformed blink samples) with condition, scaled brain

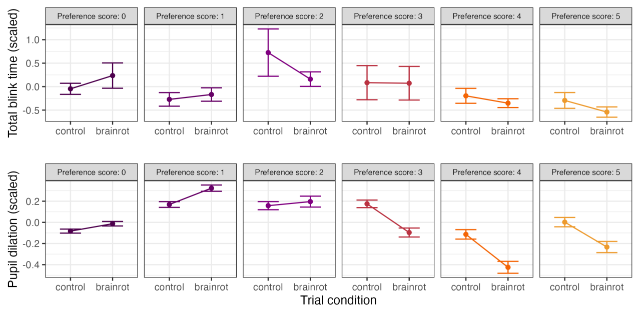

Figure 3: Preference for brain rot predicts differential blink and pupil behavior across conditions. Points are average blink time by condition (above). Points are average change in pupil size from baseline by condition (below). Error bars represent SE.

rot preference score, and condition order as fixed effects and random intercepts per participant, revealed a significant interaction between condition and preference score, (β = -0.24, t = -2.31, p = .024). This suggests that only individuals with lower preference for brain rot experience greater perceptual load while watching brain rot, reflected by their increased total blink time. The effect of preference score was significant in the brain rot condition (β = -0.28, t = -2.44, p = .02), but not in the control condition (β = 0.04, t = -0.35, p = 0.73). Total blink time is reduced among brain rot preferers in the brain rot condition only.

We also analyzed distinct eye blink events as opposed to total eye blink durations. A linear mixed-effects model predicting log-transformed blink count confirmed that higher preference results in fewer blinks in the brain rot condition (β = -0.23, t = -2.19, p = .03). In the control condition, preference did not significantly predict blink count (β = -0.11, t = -1.08, p = .28). The interaction between preference and trial condition was not significant for distinct blink events (β = -0.12, t = -1.47, p = .15). These effects remain for both blink measures after controlling for task performance and metacognitive sensitivity.

Pupil dilation indicates increased executive load during traditional content for brain rot preferers

We used a linear mixed-effects model to analyze the effects of condition and scaled brain rot preference score on participants' normalized pupil size, controlling for condition order with a random intercept for participants. The main effects of condition (β = -3.66, t = -1.04, p = 0.29) and of brain rot preference score (β = 7.77, t = 0.45, p = 0.66) were not significant. Condition order significantly predicted pupil dilation (β = 21.64, t = 5.14, p < 0.001). A significant interaction between brain rot preference score and condition (β = -40.65, t = -9.85, p < 0.001) revealed that a stronger preference for brain rot is associated with decreased pupil size while watching brain rot. These results are consistent with decades of empirical work demonstrating that pupil size increases with general cognitive load, as well as more recent evidence that pupil dilation specifically reflects increased task-related executive control demands (Gilzenrat et al., 2010; Kahneman, 1973). In line with this interpretation, increased pupil dilation in the control condition among brain rot preferers indicates increased executive demand. This suggests that attending to the control condition was more effortful for brain rot preferers.

Brain rot preferers consume more media

We assessed whether participants' digital media habits predict their preferences between the video presentations in our task. Media habit scores were approximately normally distributed (M = 3.83 out of 9, SD = 1.39, range = 0.90-7.75). Media habit score was positively correlated with brain rot preference score (Spearman's ρ = 0.35, p = .002). Media habits characterized by heavier online media consumption, higher tolerance for attentional load, and increased interest in or use of brain rot study tools were associated with a higher likelihood of preferring to learn from the brain rot video in our task. Notably, media habit scores did not independently predict task performance or metacognition in subsequent analyses.

Discussion

The incentives of digital media environments are rapidly changing the nature of the online content that we consume. Attention-grabbing "brain rot" content exemplifies this change. The term brain rot itself codifies a set of lay hypotheses, largely untested, about the potential (harmful) effects of brain rot on attention and learning. Here, we show that, counter to widespread assumptions, brain rot-style presentations of otherwise identical content led to improved learning and metacognitive sensitivity for a meaningful subset of learners. These results are in line with hypotheses that suggest that individuals learn best from stimuli that meet their specific optimal loads.

Our data on individual preferences for learning from brain rot suggest that participants are at least somewhat well calibrated in understanding the attentional demands that are optimal for their own learning. In this sense, our composite score of brain rot preference may be seen as a measure of global metacognition for brain rot. Global metacognition represents broad, more abstract self-beliefs about performance. This contrasts with local metacognition, which refers to momentary confidence in trial-by-trial performance and has overlapping but distinct neurocognitive underpinnings (Rouault & Fleming, 2020). Awareness of one's ability to learn from brain rot content is a double-edged sword. The growing use of brain rot even in educational settings may be less concerning if the primary users genuinely benefit. At the same time, a perceived dependence on high stimulation for learning may lead to disengagement from traditional educational content.

Attentional signatures of brain rot learners

Eye-tracking findings highlight two key attentional signatures associated with improved learning from brain rot. Importantly, these signatures are not a function of visual search. Neither proportion of looking time nor frequency of switches to the brain rot predicted whether participants learned better from brain rot. Instead, these performance patterns covary with two key differences in visual processing mapping onto the two-stage load theory of attention (Lavie et al., 2004). Blink responses indicate divergence in perceptual load, while pupil dilation patterns point to variation in executive load.

First, people who learn better from brain rot are less overstimulated by brain rot. More extreme blink responses correspond to higher perceptual load, or overstimulation, and brain rot learners blinked less in the brain rot condition (Bentivoglio et al., 1997). By contrast, people who learn better in the control condition demonstrate stronger signs of overstimulation in the brain rot condition, as expected (see Figure 3). Brain rot learners' apparent immunity to this overstimulation is consistent with an attentional system adapted to a higher objective ceiling of perceptual stimulation. Crucially, this variation exists despite the two groups viewing identical content, indicating that perceptual load is not objectively determined by stimulus characteristics alone. Our findings suggest that observer factors also affect perceptual load.

Second, people who learn better from brain rot exhibit higher executive load when watching content *without* brain rot. Pupil dilation indexes executive load (Beatty, 1982; Gilzenrat et al., 2010). We observed a crossover effect (see Figure 3) in which participants tended to show higher pupil dilation when watching the video from which they learned less. Brain rot learners showed higher pupil dilation in the control condition, reflecting increased expenditure of executive control to maintain attention on the control video. Speculatively, this control video was too boring for brain rot learners, i.e., outside of their optimal range of stimulation. This is striking given that the videos in the control condition were still very stimulating, with constantly changing visuals corresponding to the concepts being taught. Thus, our task may underestimate the extent of variation in attentional bandwidth within our sample. Even simpler content may produce stronger effects than we observed here.

Together, these findings lend preliminary support to an adaptive attentional bandwidth account. The range of stimulation or load that is optimal for learning may not be fixed, but rather vary across individuals. Individual adaptation shifts, but does not expand, this optimal window. This property is reflected in the performance tradeoffs we observe in our task, where ability to learn from perceptually demanding content is associated with poorer outcomes when learning from less stimulating content. Still, our paradigm relies on preexisting variation and does not establish adaptation. Future work should use longitudinal and intervention designs to test this account more directly.

Connection to real-world digital media habits

Preliminary evidence suggests that real-world digital media habits relate to preference for learning from brain rot. Specifically, we found that preference for learning from brain rot was associated with a composite score indicative of higher online media consumption, tolerance for high stimulation, and intentions to use brain rot study tools. This correlation does not establish causality, although we cautiously speculate that the relationship is complex and bidirectional. It is likely that increased short-form media consumption breeds familiarity with, and liking of, brain rot content, which in turn reinforce digital habits. Other more stable individual differences may also affect people's propensity to engage with these forms of content.

Public discourse increasingly emphasizes "resetting" attention and building tolerance to boredom through incremental exposure to "boring" tasks, like reading or even a viral TikTok challenge to do nothing (Nazaryan, 2026; Smith, 2023). These trends suggest that attention can be adapted in the opposite direction than observed in our brain rot learners, lowering the baseline stimulation needed to maintain engagement. Beyond individual practices, this discourse is part of a broader "attention activism" movement where disengagement with content is reframed as a form of resistance to algorithmically-curated feeds and content competing for attention (Burnett & Mitchell, 2025; The Friends of Attention, 2026). The adaptive account that we provide evidence for here would suggest that these movements and practices could be effective.

Limitations

Properties of our experiment and sample warrant caution when generalizing these claims. We used only two physics videos and one gameplay distractor video, so it is unclear whether these effects would replicate with other stimuli or in other domains of learning. In addition, our sample was limited to undergraduate students whose age and media habits are unrepresentative of the broader population. We suspect, for example, that other demographics may differ, both in the proportion of users whose learning would benefit from highly stimulating content and in the malleability of their attentional systems. Familiarity with brain rot content may also be necessary to accurately assess one's ability to learn from it. Finally, participants were incentivized to learn from the videos in preparation for a test, so the observed effects may differ in more naturalistic, entertainment-oriented contexts where consumption of brain rot may be more frequent.

Conclusion

We proposed an adaptive account of attentional bandwidth in which processing is best facilitated within an individual's optimal range of stimulation. We found preliminary evidence in line with this account using the brain rot trend as a test case. In general, our results indicate that an individual's optimal range of stimulation may shift, perhaps as a result of a combination of media habits and more stable individual differences.

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