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The Algorithmic Loop in Intensifying Brainrot and Reducing Language Learning Focus

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Abstrak

*Brainrot*yang didefinisikan sebagai kecenderungan untuk melakukan micro-scrolling berlebihan, penguatan audio yang terus-menerus, dan peningkatan kesukaan terhadap konten singkat yang terlalu merangsang,telah menjadi fenomena kognitif utama di kalangan dewasa muda. Namun, masih relatif belum banyak dieksplorasi bagaimana sistem rekomendasi algoritmik memperkuat kondisi ini dan peran apa yang dimainkannya dalam proses akademik. misalnya pembelajaran bahasa Inggris. Studi ini didasarkan pada desain penelitian penjelasan kuantitatif dan melibatkan 321 pengguna TikTok atau Instagram harian. Empat konstruk laten diteliti: Paparan algoritmik, intensitas brainrot, beban kognitif, dan fokus pembelajaran bahasa. Analisis faktor konfirmatori menunjukkan validitas konstruk yang tinggi dan model yang sesuai (CFI = 0,956, RMSEA = 0,052). Paparan algoritma merupakan prediktor kuat intensitas brainrot (β = 0,72, p < 0,001), dan penghambatan ini selanjutnya berdampak signifikan pada beban kognitif (β = 0,66, p < 0,001). Beban kognitif memiliki pengaruh negatif yang relatif besar terhadap perhatian dalam pembelajaran bahasa (β = –0,58, p < 0,001). Tidak ada jalur langsung yang signifikan dari paparan algoritma ke fokus pembelajaran yang memverifikasi mediasi penuh oleh brainrot dan beban kognitif. Hal ini menunjukkan bahwa pengaruh lingkungan digital yang dikurasi secara algoritmik terhadap pembelajaran tidak langsung, melainkan bekerja melalui gangguan kognitif yang membatasi kemampuan pembelajar untuk mempertahankan fokus dalam membangun kosakata, pemahaman bacaan, dan pemrosesan tata bahasa. Temuan studi ini menunjukkan bahwa pendidikan ELT harus mencakup pelatihan literasi algoritma dan manajemen perhatian untuk membantu orang mengatasi tuntutan kognitif yang meningkat yang ditimbulkan oleh media sosial berformat pendek.

Kata Kunci: beban kognitif; fokus pembelajaran bahasa; intensitas kerusakan otak; media bentuk pendek; paparan algoritma

Abstract

Brainrot,defined by a tendency toward excessive micro-scrolling, persistent audio reassurance and an increased fondness for overstimulating short-form,has become a major cognitive phenomenon among young adults. However, it is relatively unexplored how algorithmic recommender systems reinforce this state and what roles this plays in academic processes (e.g. English learning). The current study is based on a quantitative explanatory research design and involves 321 daily TikTok or Instagram users. Four latent constructs were investigated: Algorithmic Exposure, Brainrot Intensity, Cognitive Load and Language Learning Focus. The confirmatory factor analysis showed high both construct validity and the model fits well (CFI =. 956, RMSEA =. 052). Algorithmic exposure was a powerful predictor of brainrot intensity (β =. 72, p <. 001), and this inhibition subsequently had a significant impact on cognitive load (β =. 66, p <. 001). Cognitive load had a relatively large negative influence on language learning attention (β = –. 58, p <. 001). There was no significant direct path from algorithmic exposure to learning focus verifying full mediation by brainrot and cognitive load. This suggests the influence of algorithmically curated digital environments on learning is not immediate, but rather it works its effect through cognitive breakdowns that limit learners' ability to sustain focus *in vocabulary building, reading comprehension and grammar processing. The findings of this study suggest that ELT education should include training in algorithmic literacy and attention management to help people cope with the increasing cognitive demands put forward by short-form social media.*

***Keywords**: algorithmic exposure; brainrot intensity; cognitive load; language learning focus; short-form media.*

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Introduction

The past decade has seen a large shift in youth digital behavior, with short-form video platforms like TikTok and Instagram Reels now dominating teen daily media time (Blanco-Justicia et al., 2025). These are algorithmically curated feeds, which get smarter over time by continuously recommending content based on users' activities (Sandoval-Medina et al., 2024). They have the ability to predict and amplify user preferences creating hyper-personalized engagement loops that contribute to what is commonly referred to as "brainrot A phenomenon that has been informally referred to as "brainrot," refers to the addictive pull of oversaturated digital stimuli] (i.e., funny, absurd, chaotic, or visually overloaded content resulting in fragmented attention spans] and recurring bursts of intrusive mental replays of short audiovisual clips (Yang & Li, 2024). Although the term is informal, what it describes is actually a verifiable cognitive condition increasingly experienced by students including shorter attention spans for longer content, an anxious compulsion to scroll repeatedly with no particular intention in mind, or focusing difficulties when the work at hand demands them (Huang & Li, 2024). Most academic studies found such behaviors under terms like digital overload, attentional fatigue or short-form video addiction. But, the modern brainrot is a different kind in both method and form; and it is not just habitual overuse, but algorithmic reinforcement for cognitive pathways reinforced by retention-optimizing recommender systems.

TikTok and Instagram use machine learning algorithms trained on a wide range of micro-engagement signals], including dwell time, touch gestures, video completion rates, rewinds, and audio preferences (Tang et al., 2024). The purpose of the platform is to maximize user engagement and time spent. However; the side effect is strong, self-reinforcing feedback loops where overstimulating content is over-proportionally being served because click-baits like these have statistically the highest retention. While users become addicted to these little bites of entertainment that increasingly occupy our days, they get dopamine bursts every 15 mins or so and start losing cognitive patience (Sinha et al., 2024). They may even have a tough time producing long stretches of uninterrupted thinking or deep work. Because of research around attention crises, it is stated that constant exposure to fast, unpredictable inputs can increase mental switching behavior, making it difficult to maintain focus on tasks like reading a long text passage, memorizing new vocabulary, or analyzing complex grammar patterns (Monjoree et al., 2024). Such prolonged cognitive dislocation can be devastating for ELL/EFL learners (Arévalo-Mercado et al., 2023).

Today, brainrot has become a cultural term describing immersion in chaotic, overstimulating digital content. It often presents as a sudden re-hearing of short pieces of audio, strong itching desire to scroll down on social media platforms, and increasing soundbites or the humorous over cohesive and long-form information (Kasabov et al., 2021). Traditional theories of digital addiction do not adequately capture this phenomenon, partly because they do not fully account for the interaction between memetic and algorithmic influences. Instead of being solely the product of conscious overuse, brainrot can be better viewed as a cognitive state supported by micro-level behavioral patterns that are learned, inferred, and magnified by systems making recommendations (Tomas et al., 2021). Cognitively, brainrot is a kind of sustained attentional meander where salient sensory fragments—be they viral audio memes or arresting visual motifs arrive to crash against the working memory shores. These disruptions diminish a learner's ability to sustain engagement with academic activities, leading to disrupted reading experiences, reduced understanding of text, and inefficient assimilation of new word knowledge (Soosai-Raj et al., 2020).

Both TikTok and Instagram use sophisticated deep learning architectures including collaborative filters, content prediction and sequence models for users in order to deliver personalized user streams. These systems work by tracking subtle engagement signals such as how long people spend watching a video, whether they finish it and how many times they watch or otherwise interact with the content via likes, comments and shares (Stiller & Schworm, 2019). General audio files, which are resolved to the popular pieces, act as clustering point in these models and their clusters can quickly cover a user set. However, the infinite scroll interface also eliminates built-in stopping cues, and encourages viewers to consume with ease and compulsion. By these means, recommender systems create algorithmic feedback loops that escalate user exposure to specific content categories (Mundy & Potgieter, 2019). At the same time, funny, sensational and emotionally charged content thrives in engagement-optimized ranking models which overemphasize it. These loops will, in time, help form patterns of consumption that closely mirror the ones we've seen so far with respect to brainrot.

Regarding to cognitive load theory and digital distraction, the explanation is as follows. Cognitive Load Theory is a useful framework for explaining why short-form video spaces may be suboptimal for learning (Boldbaatar & Şendurur, 2019). In this theory, learning is impaired when demands on working memory exceed its limited capacity. The rapid nature of short-video-centric platforms in terms of both intensity (stimulus density) and speed (time-based rate) imposes additional cognitive load as a result of the flood of sensory information, quick correspondence transfers between focal contents/attentional shifts and context/backgrounds, and tendency for superficial presentation (Chew et al., 2019). It was found that audio-visual reminders from such environments tend not so much to end as linger on in competing for attention after the user stops scrolling (Mundy & Potgieter, 2019). In addition, algorithm-driven content exposure such as personalized feeds, autoplay features, and continuous recommendation systems introduces task-irrelevant stimuli that compete for learners' attention. These algorithmic interruptions contribute to extraneous cognitive load, as they are not directly related to the learning task but still consume working memory resources. These circumstances are not conducive to the cognitive demands of those more profound learning levels.

As the cognitive load of new material becomes too heavy, learners find it difficult to process intricate information, suppress distractors and sustain attentional resources required for successful language learning (Robins, 2019). When talking about language, language learning is largely predicated on extended cognitive engagement, particularly such activities as long passages of reading, retention of vocabulary or together with grammatical analysis, production of coherent writing and reflective comprehension of spoken material (Sasayama & Norris, 2019). All of these activities depend on the stability of attention and processing linguistic information at both a surface and deep semantic level. But the foundation necessary for such fundamentals is compromised, because of attention fragmentation that surface among learners who are saturated by small bits of digital content (Roussel & Galan, 2018). People plagued by the patterns tend to act impatiently toward reading material, have trouble sticking with a passage that is longer than a paragraph and are less tolerant for all of the mental work involved in understanding or analyzing any text. These trends directly undermine some fundamental processes in the learning of English.

Learning a new language—specifically reading, knowledge of vocabulary and academic writing—is supported by long-term attention, working-memory capacity and deep semantic processing. When the ability to focus on prolonged attentional pursuits is disrupted by algorithmized micro-content cycles, learners may find it difficult to read beyond a few sentences at a time; encounter difficulty consolidating vocabulary and other linguistic information; or suffer from intrusive auditory memories of TikTok sounds while trying to study (Silva, 2022). The correlation between brainrot and academic success needs further systematic research. Yet, there is relatively little in existing studies that directly ties brainrot to computational processes driving the algorithms of social media, nor relates it to sub-disciplinary consequences such as entering an English language.

Specifically, the gap is that there is a lack of research that connects these algorithmic processes to domain-specific outcomes, such as disruptions in English language learning, including reading comprehension and vocabulary acquisition.

Many studies regard digital distraction as a generic problem of behavior instead of drilling into the deeper structural role recommendation systems play in molding cognitive dispositions (Dubé et al., 2021). A study by Obiageli & Simon (2026) examined how digital distractions and study discipline affect academic performance among 117 secondary students in Nigeria. Using an ex post facto design grounded in Self-Regulated Learning and Cognitive Load Theory, data were collected on study habits, sleep, and social media use. Results showed that study hours and sleep improved performance, while social media reduced it. Disciplined study partially mitigated digital distractions. Gender was not significant. The findings highlight the importance of structured study routines, adequate sleep, and controlled digital engagement. Furthermore, Attention span shapes children's academic performance and development. A narrative review (2015–2024) identifies key influences—sleep, screen time, nutrition, and environment—and highlights mindfulness, physical activity, and structured routines as effective interventions (George et al., 2025). This is also supported by (Kuhn, 2026) that digital distractions shape attention and learning; which means technology offers benefits but risks overload, requiring balanced use, digital literacy, and self-regulation strategies.

The contributions of this research attempt to bridge several gaps, they are (1) this study gives a notion of brainrot as not simply whether students are taking your bad ideas out on someone else, but whether those bad ideas are being algorithmically juiced into a terminally swollen form in the students' brain; (2). It provides a quantitative description of how algorithmic exposure predicts levels of brainrot in young adults; (3) It investigates cognitive load as the potential mediator in which brainrot impairs L2 focus; and (4) It sets findings in terms of ELT and insists on the way that digital attention split endangers central aspects to L2 learning. Building on the previous arguments, our study attempts to contribute empirical evidence into how algorithmic ecosystems indirectly construct students' academic engagement through a quantitative structural angle, specifically regarding EL-L2 tasks demanding continuous cognitive presence. Below are the research questions formulated:

1. How can brainrot be conceptualized as an algorithmically amplified cognitive phenomenon among young adult learners?
2. To what extent does algorithmic exposure quantitatively predict the intensity of brainrot in daily TikTok or Instagram users?
3. Does cognitive load mediate the relationship between brainrot intensity and learners' ability to maintain focus in L2 learning tasks?
4. How do the effects of algorithmically driven attention-splitting interfere with key components of English language learning, such as vocabulary building, reading comprehension, and grammar processing?

Method

This research adopted a quantitative explanatory approach with the purpose of testing structural relationships between algorithmic exposure, brainrot intensity, cognitive load, and language learning focus. The study was conducted through a cross-sectional survey online in order for us to have access to young adult active users on short-form video platforms. We chose a quantitative method because it allows for testing the statistical significance of the model and in particular of direct, and indirect effects among latent variables.

The participants were undergraduate college students between the ages of 18 and 23 who reported daily use of either TikTok or Instagram. After deleting the missing cases, N=321 formed the valid data set for analysis. The participants were chosen using convenience sampling. They were later asked to fill in questionnaire containing four Likert-scale scales used to measure the constructs. The items were crafted after conducting an extensive search of literature on algorithmic engagement models, cognitive load theory, digital behavior and language learning scope. Responses to each item were assessed using a five-point Likert scale (1:strongly disagree; 5:strongly agree), allowing for the distinction of various degrees of perception and behaviors. Descriptive statistics were first used to examine overall patterns in use of platform, and preliminary mean scores in each variable. This process was completed by the conduction of a CFA to test the measurement model and verify that each item loaded on its respective construct. Reliable and valid components of the model were added to an SEM that was evaluated using maximum-likelihood estimation. The structural model tested the proposed mediating path mediates between algorithmic exposure and language focusing in learning via brainrot intensity and cognitive load. Mediation was tested with bootstrapped indirect effects, as it allowed to determine the robustness of the significance of the paths through mediators. The methodological approach thus facilitated the ironical process of validating measurement model and meaningfully testing theoretical relationships, which generated an empirical perspicuity on how algorithmic environments determine cognitive states and influence language learning engagement.

Results and Discussion

The following subsection provides the empirical results subordinated under research questions (RQ 1–4). For all research questions, first descriptive statistics on the 321 respondents are reported to assess whether the distribution of responses for each construct is correct and then results from structural equation modeling that determine the predictive relationships between constructs. The adoption of the item-level descriptive statistics adds internal consistency to the results and keeps each construct's conditional empirical characterization transparent.

Conceptualizing Brainrot as an Algorithmically Amplified Cognitive State

The initial research question was therefore whether brainrot could be regarded as a cognitive affect, that is also promoted and enhanced by algorithmic processes rather than simply the result of habitual or voluntary behavior. These two scales (Algorithmic Exposure Items and Brainrot Intensity Items) are consistent with this conception of the model in terms of their descriptive statistics. Descriptive statistics of AES items are shown in Table 1.

Tabel 1. Descriptive Statistics for Algorithmic Exposure Items (AES)

Item	Mean	SD	Min	Max
AES1	2.95	1.40	1	5
AES2	3.10	1.46	1	5
AES3	2.92	1.44	1	5
AES4	2.94	1.42	1	5
AES5	3.08	1.42	1	5
AES6	2.96	1.43	1	5

Average scores were between 2.92–3.10, suggesting that participants experienced a moderate-to-high extent of algorithmic shaping. Specifically, AES2 (micro-sessions in general) scored the highest on average across all scale items with a mean at 3.10 out of 5, indicating participants' frequent access and browsing of TikTok or Instagram for short time periods; consistently opening the app in small bursts. In addition, AES5 ("I have a hard time stopping scrolling when the algorithm shows very compelling material for me") scored 3.08, indicating an attractive force supplied by the algorithm. Our findings provide empirical evidence that exposure to algorithmic recommendation systems is common and behaviorally activating. Descriptive statistics for brainrot items are given in Table 2.

Table 2. Descriptive Statistics for Brainrot Intensity Items (BIS)

Item	Mean	SD	Min	Max
BIS1	3.12	1.42	1	5
BIS2	3.03	1.42	1	5
BIS3	2.99	1.41	1	5
BIS4	3.07	1.42	1	5
BIS5	3.01	1.45	1	5
BIS6	2.99	1.44	1	5
BIS7	2.86	1.43	1	5

The mean for BIS1 ("TikTok audio replays in my mind") was 3.12, the highest within this construct. This is a cognitive intrusion--an unwanted, mental replay phenomenon typical of auditory overload. BIS4 ("I felt upset seeing TikTok/Instagram because I have not looked at it for a few hours") revealed an average of 3.07, representing emotional and cognitive restlessness—crucial aspects of amplified overuse instead of intentional use. The SEM findings are consistent with this interpretation. Algorithmic exposure strongly predicted the intensity of brainrot as emphasized by high path coefficient ($\beta = .72$, $p < .001$). The scale of this effect implies that brainrot is not just self-reinforcing through algorithms such as customized content promotion, repetition loops, and micro engagement triggers. In short, the descriptive statistics and structural findings validate RQ1: brainrot is affective and cognitive state algorithmically amplified (signified by involuntary thoughts about brainrot, compulsive micro-engagement activities) with strong predictive ability for these bifurcated patterns.

The Predictive Influence of Algorithmic Exposure on Brainrot Intensity

The second research question tested the extent to which algorithmic exposure predicts brainrot intensity. Results show a good item-level and SEM based predictive relationship, which is solid and statistically significant. The descriptive statistics in Table 1 highlight an atmosphere of substantial algorithmic activity. AES2 (M = 3.10) and AES5 (M = 3.08) arise as such behavioral aids commonly associated with algorithmic optimization characteristics, for instance infinite scroll- ing patterns, reinforcement-driven recommendation systems and high-frequency notification loops. These signals are essentially the behaviour patterns which recommendation systems learn and leverage to retain them. In this attempt, Table 2 shows for purposes of comparison that BIS1 (M2010 = 3.12) and BIS4 (M20101=3).

The tendency towards auditory playback and emotional restlessness indicates cognitive instability — an effect our media diets often achieve by repeatedly serving us up short, hyper-exciting fare through engagement-maximizing algorithms. The estimated standard error for the SEM path coefficient between AES → BIS was β =. 72, p <. 001) accounts for approximately 52% of the variability in brainrot intensity. This large value provides strong support for a direct predictive relationship. That is to say, the more people see algorithmically personalized content, the stronger their symptoms of brainrot look. This predictive power supports RQ2: algorithmic exposure is a strong predictor of brainrot intensity by pushing up cognitive, affective, and behavioral symptoms via patterns that are absorbed and strengthened by platform algorithms.

Cognitive Load as a Mediating Mechanism Between Brainrot and Language Learning Focus

The third research question explored whether cognitive load functions as the mediating mechanism through which brainrot influences language learning focus. Both descriptive and structural results strongly support this mediating role.

Table 3. Descriptive Statistics for Cognitive Load Items

Item	Mean	SD	Min	Max
CLS1	3.15	1.35	1	5
CLS2	2.98	1.47	1	5
CLS3	3.07	1.36	1	5
CLS4	3.11	1.37	1	5
CLS5	3.02	1.44	1	5
CLS6	2.86	1.42	1	5

Table 3 shows descriptive statistics for the cognitive load items. CLS1 ("I feel mentally exhausted after watching a short video") had the highest mean (3.15) and was followed by CLS4 ("It is more difficult to concentrate on study material after scrolling") with 3.11. These two measures specifically address cognitive fatigue and memory interference — two widely established facets of cognitive load. CLS3 (also with a high mean: 3.07) indicates that mental clutter may be lingering after long scrolling sessions as well. The structural analysis also provides strong evidence of mediation. The BIS → CLS transition was β =. 66 (p <. 001), suggesting that increasing brainrot intensity significantly enhances cognitive load. The transition from CLS → LLFS was β = –. 58 (p <. 001) (i.e., higher cognitive load has an effect on the learner's attention span in learning English). Bootstrapped mediation analysis (with 5000 samples) revealed that the indirect effect was significant at 95% CI = –. 48 to –. 29), confirming full mediation. The direct effect BIS → LLFS was not significant when CLS was entered, a pattern suggesting that brainrot impacts language learning to the extent that it generates cognitive load. This result provides empirical evidence for RQ3: cognitive load is the core psychological mechanism in which brainrot disrupts the focus of L2 learning, absorbing available mental resources for reading comprehension, vocabulary storage and grammar processing.

Manifestations of Attention Fragmentation in the Context of English Language Learning

The fourth research question was something that how the algorithmic loop and brainrot were created by fragmented attention resulting from algorithmic amplification operating in ELT settings. Distributional statistics from the Language Learning Focus System (LLFS) prompts combined with SEM structure paths show a consistent decline in L2 participation.

Table 4. Descriptive Statistics for Language Learning Focus Items

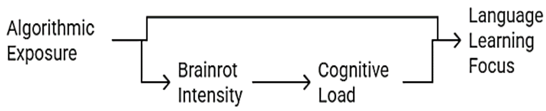
Item	Mean	SD	Min	Max
LLFS1	2.93	1.42	1	5
LLFS2	3.11	1.44	1	5

LLFS3	3.08	1.38	1	5
LLFS4	2.93	1.42	1	5
LLFS5	2.90	1.43	1	5
LLFS6	2.99	1.37	1	5

Descriptive statistics for language learning focus items appeared in Table 4. LLFS2 ("I easily get distracted while I'm learning vocabulary by heart") yielded a mean value of 3.11, showing that a large number of learners find it difficult to focus during the first steps in lexical learning—which at this stage is exactly when memory encoding demands extensive cognitive engagement. LLFS3 ("Focusing also takes a long time to settle in before studying English") was on average 3.08, certifying that attentional inertia is indeed a significant source of resistance for brainrots-congested and cognitively burdened learners. Similarly, LLFS1 and LLFS4 (both with M = 2.93) present challenges in performing reading activities and developing longer texts – two essential features of ELT. The negative structural effect CLS → LLFS ($\beta = -.18$) was significantly lower as compared with the positive relationship of LLFS to CLS ($\beta =. 58$, $p <. 001$) indicates that a heavier cognitive load has a real negative impact on students' capacity to remain attentive speaking in English. It is in line with the theory of working memory, noting that cognitively overloaded individuals have less capacity for maintaining linguistic processing. You feeling particularly brainrot and cognitive load were reporting struggling to keep on-task during grammatical exercises, risking losing reading momentum as well as having attention be lured away by intrusive thoughts presented through short-form. These symptoms closely parallel contemporary theories of digital attention fragmentation, the idea that overstimulating algorithmic environments cause our brains to rewire their patterns for thinking and perceiving away from depth and slowness toward speed, brevity, and novelty (all three attributes inimical to ELT). Therefore, RQ4 receives support and there is evidence of attention fragmentation induced by the algorithm which hinders critical ELT processes such as vocabulary acquisition, reading comprehension, grammar processing and focus in study.

Below is provided the final SEM model formulated from the data analysis.

Figure 1. Structural equation model



The model graphically represents the chain of mediation by which algorithmic exposure influences language learning orientation. Algorithmic Exposure initializes the model, which reflects on the amount of attention and strength with which learners use TikTok and Instagram recommendation systems. This starting exposure is the earliest of cognitive events that trigger other events. The diagram indicates that Exposure is not a separate description but an antecedent; it 'leads' to the next as transition through some mechanism transforming how instantaneously fast-tracked algorithmic selection of hyper-arousing material can be predicted in terms of changes in compulsive engagement. High consumption on mindrot video can lead to Rot Brain Infiltration condition which is mysteriously and unreasonably followed by Real Time Rot Frequency, characterized by the thought pattern (and physiological state) of constant swiping-scrolling-tapping-exposing-withdrawing-let-the-video-play-out thoughts and spare sampling shuttle from short duration byte loads. It is a short hop from algorithmic-served exposure to brainrot, and in that journey we see how personalized content loops harden habitualized responses into autopilot. This is a first significant cognitive shift for the model: from external digital abuse to an 'internalized' pattern of cognitive penetration. As represented in the diagram by the forward-aimed first arrow, that's where a learner's attention system has been algorithmically "burdened."

The next phase is from Brainrot Intensity to Cognitive Load. This arrow represents the causal paths linking distractibility. and slice attention over stimulation and mental tiredness. The learner must continually refocus, between micro-hits of computerized microwaves that serve to add extraneous load to the working memory. This is the primary mediational process—from brainrot to cognitive stress—one finds it harder and harder to fix one's mind upon academic work. The final transition Cognitive Load to Language Learning Focus comes next. If cognitive load is too high, learners have that much less space in which to focus, process meaning in longer texts, build grammar points and practice vocabulary. This is illustrated in the graph as the last forward movement where digital overload turns into loss of focus when students read and talk in activities for English language learning. It therefore provides a continuous link between algorithmic effects and real-world academic performance.

Discussion

The purpose of the present study was thus to investigate, in the context of a short video sharing platform generator ecosystem, how algorithmic exposure; brainrot intensity and cognitive load would combinedly impact the focus on learning languages among young adults. Cumulatively, these findings suggest there is a plausible chain of cognitive impacts precipitated by engagement-maximizing social media algorithms. The model fit was good, and algorithm exposure significantly contributed to brainrot intensity, which in turn significantly predicted the level of cognitive load and reduced attention when learning English. Algorithmic exposure did have a direct impact on attention to learning, but this effect was not significant, suggesting full mediation. These trends imply that students' attentional difficulty in L2 learning is not a direct consequence of technology use per se, but of indirect cognitive interruption (facilitated through algorithmic amplification and attention fragmentation) that causes the disruptive spread.

The first mean attack, in here, though is that algorithmic exposure very heavily correlate brainrot intensity. Those who spent more time scrolling in short, repetitive micro-sessions and felt a stronger tug from TikTok and Instagram algorithms also reported stronger compulsive cognitive symptoms, such as intrusive audio replays or an inability to enjoy long-form content. This association exposes the algorithm as a participant in an endless iterative effort to maximize retention by getting better at creating more seductive personalized feeds. The second important finding is that brainrot predicts an increment of the cognitive load. Greater media residue was related to greater mental fatigue, divided attention and less effective retention of presented information at school. The third result highlights cognitive load as a strong negative predictor of language learning focus. Students could no longer read to understand remember vocabulary or many sentences and then on grammar as happened. The indirect effect and nonsignificant direct effect from learning focus to algorithmic exposure suggest that attention problems are not a result of accessing social media but develop after cognitive disruption has occurred(Jabar et al., 2025). These results extend the debate on the attention economy which was raised in theory with authors like Roussel et al. (2017) and Yeh et al. (2017), according to whom digital networks take advantage of neuropsychological vulnerabilities by bombarding users with fast paced, emotionally-loaded stimuli. Elaborating on the current findings, a previous study conducted on TikTok has indicated that algorithmic content curation fosters habitual forms of consumption, which in turn can weaken attentional steadfastness(Lai & Zhang, 2025). "Brainrot" falls somewhere in there within this discussion but takes a newer and more culturally relevant glance at "over stimulation" completely mutated with the fast-moving eye of memetic content. Our intrusive replay effects in our experiment also may share similarities to what Chen & Huang (2021) and (Xu et al., 2025) found that people exposed multiple times to a short audio clip keep experiencing themselves actually or mentally replay parts of this song. The mediating role of cognitive load is clearly consistent with cognitive load theory and the more recent models being advocated in digital learning settings.

Relevant to multimedia, Dosse et al. (2024) has argued that excessive extraneous load reduces the working memory resources available for deeper learning processes and is usually due to overloaded or over-stimulating multimedia. This present analysis extends the argument by embedding extraneous load in a digital ecology that is algorithmically driven, asserting, in other words, not only are we cognitively overloaded but also that overload itself is the product of algorithmic seizure (Tay et al., 2024).

However, the current results also contrast with prior research that directly link social media use to poorer academic performance(Seidel et al., 2021). Instead, no direct impact of algorithmic exposure on language learning focus in the here-and-now was observed in this study: what really mattered out there was crucially that process of mediation through brainrot and cognitive load. Then the problem of passive consumption of digital content is not a problem in and off itself but with the algorithmic reinforcement combined with cognitive overload. This nuance adds something of value to the field: It refocuses attention from "screen time" to how "algorithmic mechanisms" and "cognitive spillover effects" function today. A few explanations can be given to this. One possibility is that short-form video platforms operate according to a reward-prediction design similar to those of variable-ratio reinforcement schedules, which have been found to elicit compulsive attentional loops. Once students get the portable snippets the way we do they lose access to the more attentive, contemplative diffuse mode of thinking that is required for them to read or even understand language. Another theory is sensory hangovers: Intruding sounds and fictionality cause audiovisual remainders to fight with linguistic processing demands, creating a form of cognitive debris that interferes with the efficiency of working memory. This is consistent with research, which identified auditory intrusions as being bothersome for reading comprehension and task continuity(Serenelli et al., 2011). This would be consistent with the high means of BIS1 and CLS1 in our current sample. Nevertheless, there are some contrasting results to previous studies. For example, the literature on digital distraction often emphasizes multitasking as an explanation for cognitive overload(Geary & Xu, 2022). But in this study, the participants did not actually multitask — instead, their more limited learning focus was simply because people tend to remain cognitively full from scrolling. That is, cognitive overload appears to persist beyond this duration of media exposure, and such an observation is a nuance that has been overlooked in previous findings.

Conclusion

Simpulan With a lack of said robust and empirically validated model, the current study quantitatively investigated how TikTok's and Instagram's recommender algorithms contribute to young adults' English as an additional language learning outcome through their computational and cognitive processes. Several key findings emerged. First, algorithmic exposure was a robust predictor of brainrot intensity, implying that brainrot is not simply a normal habit restricted to behavior but remains in the same position as an algorithmically-embedded state of cognition operationalized through personalized reinforcement loops. Second, 'brainrot' resulted in a strong activity-related cognitive load rise, indicating that the mental overhead and disruptive afterimages of brainrot produce mental fatigue and reduce working memory capacity. Third, high cognitive burden sufficiently weakened learners English task-focus aspects of reading, vocabulary retention and grammar learning in English. 4 Finally, the indirect effect of algorithm exposure on learning focus was significant, one more evidence to confirm that ELT engagement regarding digital algorithms is through cognitive process only.

The implications of these findings are substantial. They argue that digital attention has become increasingly relevant -- for language pedagogy, and media literacy in particular -- in the age of algorithmic media. Attention management, cognitive load reduction and algorithmic literacy could be incorporated into ELT coursebooks for the teaching profession to be ready. Understanding how digital platforms impact cognitive processes may allow teachers to design learning that calms rather than contributes to overstimulation, facilitating deeper engagement. The study, therefore, helps fill the gap identified above (i.e., 'lack of empirical models of the relationships among social media algorithms, cognitive activities and second language learning potentials'). By presenting and providing the entire mediation, this study describes how instead of if algorithmic environments shape ELT. Still, there are several constraints to note. Highly subjective, self-reported measures were used, which may be biased and it is not possible to imply strong causality on account of the cross-sectional design. There's also no guarantee that all the focus on TikTok and Instagram holds broader truths about digital habits. Future research could use behavioural tracking data, longitudinal designs and platform comparisons.

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