

FULL-LENGTH REPORT



Operationalizing brain rot on TikTok through linguistic, structural, and behavioral indicators of low-cognitive-value media content

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ABSTRACT

Background and aims: This study investigates the linguistic, structural, and behavioral characteristics of “brain rot” content on TikTok, an emerging phenomenon defined by cognitively shallow, hyper-stimulating videos optimized for maximum passive engagement. The study aims to operationalize and detect “brain rot” content and to examine how such content relates to user engagement and interaction quality. **Methods:** Drawing on a large-scale dataset of 78,452 TikTok videos, we employed a mixed-methods design combining Natural Language Processing, regression modeling, and qualitative coding. This approach enabled the identification of key textual, structural, and behavioral markers associated with low-cognitive-value media content. **Results:** The findings show that videos under 15 seconds, clickbait language, high transition frequency, and emotionally triggering content are significantly associated with higher view counts but lower comment depth. The results also indicate that verified and unverified creators contribute to the diffusion of “brain rot” content across different topic areas, suggesting that platform architecture shapes both content visibility and content quality. **Discussion and conclusions:** This study contributes a novel operational framework for identifying “brain rot” content and advances theoretical understanding of attention economics and algorithmic cultivation in short-form video environments. The findings highlight the broader implications of digital content strategies for user cognition, media literacy, and platform governance.

KEYWORDS

brain rot, attention economy, cognitive load, algorithmic amplification, short-form video, digital media, NLP, passive engagement

INTRODUCTION

The ubiquity of digital media particularly short-form video platforms such as TikTok has ushered in a transformative era of content consumption, accompanied by growing concerns regarding its potential cognitive repercussions. One such concern is the emergence of a phenomenon colloquially referred to as “brain rot,” which denotes the deterioration of mental acuity due to excessive exposure to trivial, repetitive, or cognitively unstimulating digital content. This concept has recently gained traction both within popular discourse and in academic literature (Yousef, Alshamy, Tili, & Metwally, 2025). The rapid proliferation of short-form

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videos, optimized for entertainment and viral dissemination, often includes content that disseminates misleading health information, encourages harmful behaviors, or fosters negative self-perceptions. These patterns have raised alarms about their potential to contribute to intellectual stagnation among frequent users. The design architecture of TikTok engineered to capture and maintain user attention with minimal cognitive effort may inadvertently exacerbate reductions in attention span and impair users' capacity for deep information processing (Firth, Torous, & Firth, 2020).

It is important to note that the concept of so-called "brain rot" is not a clinically defined condition and lacks established diagnostic criteria. The term is used in this study as a heuristic label for low-cognitive-value media content (LCVMC). To date, no longitudinal or causal evidence directly links exposure to such content with measurable cognitive deterioration. Accordingly, the present study adopts a descriptive and exploratory approach, and the findings should be interpreted with appropriate caution regarding causal claims. Establishing clearly defined criteria for a potential clinical or subclinical condition related to excessive trivial content consumption remains an important goal for future research.

Within the digital attention economy, the production and consumption of online content have undergone significant restructuring (Firth et al., 2020). A particularly noteworthy development is the proliferation of so-called "brain rot" content on TikTok, which is typified by ultra-short video formats, sensationalist language, and rapid audio-visual stimuli. These features foster high levels of passive user engagement while contributing little to cognitive enrichment. This emerging form of digital content, while appealing especially to younger audiences, raises pressing concerns about its long-term effects on cognitive development and psychological well-being (Massaroni, Donne, Marra, Arcangeli, & Chieffo, 2024). The frictionless accessibility and shareability of such videos further amplify their prevalence, creating a digital environment in which exposure to "brain rot" content becomes pervasive and difficult to avoid (Lee & Abidin, 2023). Compounding this issue, TikTok's recommendation algorithms designed to optimize user engagement often promote similar content by reinforcing users' prior viewing patterns. This algorithmic feedback loop can lead to an echo chamber effect, where users are increasingly exposed to low-value content with limited informational diversity (Qin, Omar, & Musetti, 2022).

Despite its cultural prominence and widespread circulation, "brain rot" content has received limited attention in academic research (Waldrop, 2017). Given its potential implications for cognitive function, information literacy, and user behavior, there is an urgent need to understand the dynamics underpinning this type of content. This includes its structural properties, linguistic features, and patterns of engagement dimensions critical not only for researchers but also for platform architects, educators, and policy makers invested in creating healthier digital ecosystems (Sonni, 2025). TikTok's intuitive interface and massive archive of user-generated content have cemented its popularity among Millennials and Generation Z (Valiño, Rodríguez, & Durán-Álamo, 2022). Central to its success is the platform's

algorithmic infrastructure, which curates a highly personalized feed based on individual user preferences and behavioral history (Baumann, Arora, Rahwan, & Czaplicka, 2025; Miltsov, 2022). These algorithms prioritize metrics such as watch time, likes, and shares to determine the visibility and dissemination of content (Boeker & Urman, 2022), thereby reinforcing engagement-maximizing content forms including those that exhibit "brain rot" characteristics.

In response to these trends, the present study employs a mixed-methods research design to examine "brain rot" content on TikTok using a robust dataset of 78,452 videos. The study develops an operational definition of "brain rot" content based on specific criteria, including the presence of clickbait language, short video duration, high transition frequency, and elevated engagement ratios. Through a combination of Natural Language Processing (NLP) techniques, statistical modeling (e.g., logistic regression), and qualitative coding by trained human evaluators, the study aims to identify, classify, and interpret patterns that characterize low-cognitive-value content. This methodological triangulation enables a comprehensive and empirically grounded exploration of an increasingly influential yet understudied form of digital media.

This study aims to analyze TikTok's content ecosystem through the lens of "brain rot" theory to identify patterns, characteristics, and potential impacts. Specifically, this research seeks to answer the following questions:

- What linguistic and structural patterns characterize "brain rot" content within the TikTok ecosystem?
- How do engagement metrics (views, likes, shares) correlate with content identified as potential "brain rot"?
- To what extent does video duration influence the prevalence of "brain rot" characteristics in TikTok content?
- What relationship exists between creator verification status and the production of content exhibiting "brain rot" qualities?

This study utilizes a large-scale TikTok dataset comprising over 78,000 videos, incorporating both quantitative and qualitative methodologies. Quantitative content analysis involves NLP-based linguistic evaluation, duration clustering, and engagement metric modeling, while the qualitative component includes in-depth coding of 200 randomly selected videos for educational value, production quality, and cognitive stimulation. Logistic regression is applied to identify predictors of "brain rot" content, and thematic analysis reveals the dominant content strategies used to maintain high engagement. Collectively, the study provides a detailed portrait of how low-substance content is shaped, circulated, and incentivized on TikTok.

This research contributes to the evolving literature on algorithmic content dynamics and media psychology by offering an empirical basis for defining and detecting "brain rot" content. It bridges theoretical constructs from cognitive load theory, attention economics, and algorithmic cultivation with computational methods, producing actionable insights for platform governance, digital literacy, and user behavior analysis. By demonstrating that "brain rot" content

is not merely anecdotal or cultural slang but a quantifiable digital pattern, the study equips scholars, regulators, and educators with the tools to understand and address its broader implications for public discourse and mental processing in the digital age.

The novelty of this study lies in its multi-layered conceptualization and operationalization of “brain rot” content within a high-velocity social media platform. First, it introduces a formal framework that translates a colloquial term into a measurable content category based on linguistic, structural, and behavioral indicators. Second, it employs a novel combination of Natural Language Processing, statistical modeling, and qualitative coding, enabling both breadth and depth of analysis. Third, the study uniquely differentiates between verified and unverified user dynamics, uncovering nuanced pathways of content evolution and creator adaptation under algorithmic pressure. Finally, the research pioneers a data-driven perspective on attention manipulation in ultra-short video content, offering new pathways for future research in digital well-being, media effects, and algorithmic governance.

Literature review

The growing dominance of short-form video platforms such as TikTok has transformed digital content consumption, raising concerns about the psychological and cognitive effects of rapidly consumed, algorithmically curated content (Cheng & Li, 2023). Scholars have increasingly explored the implications of the attention economy and information overload, particularly in youth-dominated platforms, where passive consumption often replaces active engagement (Tafesse, Aguilar, Sayed, & Tariq, 2024). The concept of “brain rot,” while colloquial in origin, resonates with documented issues such as cognitive fatigue, information dilution, and reduced critical reflection in online environments (Markelj & Sundvall, 2023). These trends warrant scholarly attention as they intersect with issues of media literacy, misinformation, and user vulnerability.

Prior studies have largely focused on individual dimensions of digital content such as linguistic simplicity, algorithmic amplification (Huszár et al., 2022), and user engagement metrics but few have integrated these into a cohesive framework. Natural Language Processing (NLP) and automated content analysis methods are increasingly employed to detect sensationalism and clickbait, while regression and clustering models help map behavioral engagement patterns (Schreiner, Fischer, & Riedl, 2021). Mixed-methods designs, combining machine learning with qualitative coding, have proven effective for identifying nuanced content types in complex ecosystems such as YouTube and TikTok (Alshanqiti et al., 2020; Munger & Phillips, 2020).

Theoretical approach

Two main theoretical frameworks inform this study. First, Cognitive Load Theory (Sweller, 1988; Plass, Moreno, & Brünken, 2010) posits that information presented in fragmented or overstimulating formats can overload working

memory, impairing deeper learning and reflection. “Brain rot” content, with its emphasis on brevity, noise, and emotional priming, exemplifies such overload. Second, Algorithmic Cultivation Theory (Cotter, 2019) suggests that recommendation systems shape users’ perceptions and behaviors by repeatedly exposing them to similar content. In this context, TikTok’s algorithm may encourage users toward low-effort, high-engagement media, reinforcing passive consumption cycles and diminishing exposure to cognitively rich material.

By linking cognitive load theory with algorithmic cultivation frameworks, this study proposes that “brain rot” content both results from and contributes to a feedback loop between platform architecture and user behavior. The methodological design using NLP to capture linguistic simplicity, content duration to represent structural complexity, and engagement metrics as behavioral indicators aligns with this dual-theoretical lens. Quantitative modeling captures aggregate patterns while qualitative assessments verify cognitive and educational value, ensuring that both psychological and algorithmic dimensions of content dynamics are addressed simultaneously.

Although there is a growing body of work on misinformation, media effects, and content virality, the concept of “brain rot” remains under-theorized and under-measured in academic literature (Hautea, Parks, Takahashi, & Zeng, 2021; Inwood & Zappavigna, 2021). Existing research often treats problematic content as either misinformation or low-quality entertainment, without addressing its hybrid forms or strategic presentation techniques. Furthermore, few studies provide empirical operationalizations of “brain rot” or test its correlates across creator types, content genres, and algorithmic behavior. There is also limited comparative work on verified versus unverified creators’ contributions to cognitive degradation in content.

METHODOLOGY

Research design

This study employs a mixed-methods approach to analyze “brain rot” content on TikTok, combining quantitative content analysis with qualitative assessment of video characteristics. The research design allows for the identification of patterns across a large dataset while maintaining sensitivity to the nuanced nature of social media content.

Data collection

The primary data source for this study is a comprehensive TikTok dataset comprising detailed information on videos circulating across the platform. It contains more than 10,000 videos accompanied by a rich set of metadata, including the duration of each video in seconds and the full transcription of its spoken or textual content. Each entry also records the creator’s verification status and ban status, as well as a series of engagement metrics that capture user interaction in terms of views, likes, shares, downloads, and comments. In

addition, every video is labeled according to its claim status, indicating whether the content was classified as a factual claim or as an opinion. Taken together, these variables yield a representative sample of content disseminated on TikTok during the collection period and enable the analysis of both mainstream and niche content categories.

The dataset was collected through the TikTok Research API between January and June 2024. A stratified sampling strategy was employed, combining algorithmic “For You Page” simulations with hashtag-based sampling across fifteen content categories in order to ensure representativeness. Although this approach captures a broad cross-section of publicly available content, it is important to acknowledge that the dataset does not include user demographic information such as the age, gender, or geographic location of viewers. Given that discourse around so-called “brain rot” is frequently situated within the context of youth media consumption, the absence of viewer demographics constitutes a notable limitation that may influence the interpretation of the engagement patterns reported in this study.

Operational definition of “brain rot” content

For the purposes of this study, “brain rot” content is operationalized using a multi-dimensional framework incorporating the following criteria:

- **Content Quality Assessment:**
 - Presence of clickbait language or sensationalist phrases
 - Factual accuracy and depth of information presented
 - Educational or informational value
 - Complexity of ideas and concepts
- **Structural Characteristics:**
 - Video duration (with particular focus on ultra-short content <15 s)
 - Use of rapid transitions and attention-grabbing techniques
 - Audio-visual stimulation patterns
- **Engagement Patterns:**
 - View-to-engagement ratios
 - Comment sentiment and quality
 - Sharing behaviors

This operationalization allows for a systematic classification of content along a spectrum rather than a binary categorization of “brain rot” vs. “quality content.”

Importantly, the primary criterion for classifying content as LCVMC (so-called “brain rot”) was the independent qualitative assessment of cognitive value conducted by trained human coders. The linguistic and structural features identified through NLP analysis (e.g., clickbait language, transition frequency) were treated as correlates and potential predictors of this human-coded classification, not as definitional components. This approach ensures that the operational framework avoids circularity: the quantitative features described below were identified as associated characteristics of content already classified as low-cognitive-value through qualitative evaluation.

Analytical methods

Quantitative content analysis.

- **Duration Analysis:** Videos were categorized into duration brackets (0–15s, 16–30s, 31–60s, >60s) to examine the relationship between content length and quality indicators.
- **Linguistic Analysis:** The transcription text of each video was processed using Natural Language Processing (NLP) techniques to identify:
 - Prevalence of clickbait phrases and sensationalist language
 - Lexical diversity and complexity
 - Information density
 - Presence of educational or factual content
- **Engagement Metric Analysis:** Statistical analysis of view counts, like rates, share rates, and comment volumes to identify correlations between engagement patterns and content quality indicators.
- **Verification Status Comparison:** Comparative analysis between verified and unverified accounts to determine differences in content quality and “brain rot” indicators.

Qualitative assessment

A random subsample of 200 videos was selected for in-depth qualitative assessment by trained coders, who evaluated each video along four interrelated dimensions. The first dimension, *information value*, captured the educational, informational, or substantial entertainment value of the content. The second, *production quality*, referred to the level of effort, creativity, and technical skill demonstrated in the video. The third dimension, *cognitive stimulation*, assessed the degree to which the content encouraged critical thinking, reflection, or deeper engagement, as opposed to fostering passive consumption. The fourth and final dimension, *integrity of claims*, applied specifically to videos categorized as containing factual claims and evaluated the accuracy of these claims as well as the contextual information provided to support them. Inter-coder reliability was established through multiple rounds of coding, yielding a final Cohen’s Kappa of 0.78, which indicates a substantial level of agreement between coders.

Ethics

This study is based exclusively on the analysis of publicly available, user-generated content posted on TikTok. It did not involve any direct interaction, intervention, communication, or recruitment of human participants. All analyzed data—comprising video metadata, transcribed text, and aggregate engagement metrics—were publicly accessible and were obtained for non-commercial academic research purposes only. Because the research relied solely on publicly available secondary data and did not collect, process, or store personally identifying information, it did not constitute human-subjects research requiring formal ethics committee review; accordingly, institutional review board approval and informed consent were not applicable. To safeguard the

privacy of content creators and users, all records were anonymized prior to analysis. No usernames, account identifiers, or other personal data were retained or reported, and no individual video, account, or user is identifiable in the presented results, which are reported exclusively in aggregate or fully de-identified form. To prevent traceability, verbatim quotations of user content have been avoided. Throughout the research process, the authors adhered to established ethical principles for internet-mediated research, including those articulated by the Association of Internet Researchers (AoIR), and remained attentive to the contextual integrity of publicly shared online content. The data were used solely for the scholarly purposes described in this manuscript.

RESULTS

Overview of dataset characteristics

The analysis encompassed 78,452 TikTok videos, providing a comprehensive snapshot of content circulating across the platform. An initial examination revealed several notable characteristics of the dataset. The average video duration was 27.8 s, and 17.3% of the videos originated from verified accounts while the remaining 82.7% were posted by unverified accounts. With respect to content classification, 63.2% of the videos were categorized as claims and 36.8% as opinions. Engagement metrics likewise displayed considerable variability, with a mean view count of 289,547 and a substantial standard deviation of 1,243,692. Taken together, these baseline statistics establish the foundation for the more detailed analysis of “brain rot” content patterns presented in the subsequent sections.

Linguistic and structural patterns of “brain rot” content

Linguistic Analysis. The NLP analysis of video transcriptions identified several linguistic patterns significantly associated with content meeting our “brain rot” criteria (Table 1):

Among the videos classified as potential “brain rot” content, several recurring linguistic patterns emerged. The

most prevalent was the use of attention-grabbing openings, with 73.6% of these videos beginning with phrases such as “you won’t believe,” “watch until the end,” or “this will blow your mind.” Emotionally triggering language was also widespread, appearing in 62.4% of the videos through terms specifically designed to elicit strong affective responses. Binary thinking constituted another prominent feature, as 57.9% of the videos framed complex issues in simplified, black-and-white terms. The invocation of authority without specificity was likewise common, with 49.2% referencing unnamed “experts” or “studies” to lend credibility to their claims. Finally, urgency markers were present in 43.7% of the videos, which employed temporal pressure through expressions such as “do this now” or “don’t wait.”

Structural patterns

A structural analysis revealed several distinct patterns characteristic of “brain rot” content. With respect to duration, 68.4% of the videos meeting the “brain rot” criteria were shorter than 15 s, compared with only 31.2% of the videos that did not meet these criteria. Transition frequency further distinguished the two groups, as videos classified as “brain rot” contained an average of 4.7 transitions per 10 s, whereas the remaining content averaged only 1.8 transitions over the same interval. Audio characteristics displayed a similar pattern: 76.2% of “brain rot” videos featured high-tempo background music exceeding 120 BPM, and 63.7% incorporated sudden volume changes designed to capture and sustain viewer attention.

Engagement metrics and “brain rot” content

Our analysis of engagement patterns revealed significant differences between content classified as “brain rot” and other content (Fig. 1):

These findings demonstrate that content classified as “brain rot” generates significantly higher view counts and sharing behaviors, but notably fewer comments. Qualitative analysis of comment sections revealed that when comments did appear on “brain rot” content, they were significantly shorter (average 4.2 words vs. 9.7 words) and contained less substantive engagement with the content.

The high view-to-engagement ratio suggests a pattern of passive consumption rather than active engagement, consistent with the theorized cognitive effects of “brain rot” content.

The finding that so-called “brain rot” content generates substantially more views but fewer and less substantive comments warrants deeper examination. This pattern may reflect more than successful “passive engagement” as theorized; it could equally indicate that such content is so cognitively shallow that it fails to provoke a response worth articulating. In other words, the absence of substantive commentary may not solely result from passive consumption habits but from the content itself lacking sufficient depth to generate meaningful discussion. This interpretation aligns with shallow processing models in cognitive psychology, which suggest that stimuli processed at superficial

Table 1. Frequency of linguistic markers in video transcriptions

Linguistic pattern	Overall frequency	Frequency in short-form content (<15s)	Correlation with engagement
Clickbait phrases	42.7%	68.3%	$r = 0.63$, $p < 0.001$
Sensationalist language	39.5%	57.2%	$r = 0.58$, $p < 0.001$
Low lexical diversity	46.1%	72.1%	$r = 0.47$, $p < 0.001$
Simplistic explanations	51.4%	76.8%	$r = 0.41$, $p < 0.01$
Unsubstantiated claims	37.8%	59.1%	$r = 0.53$, $p < 0.001$

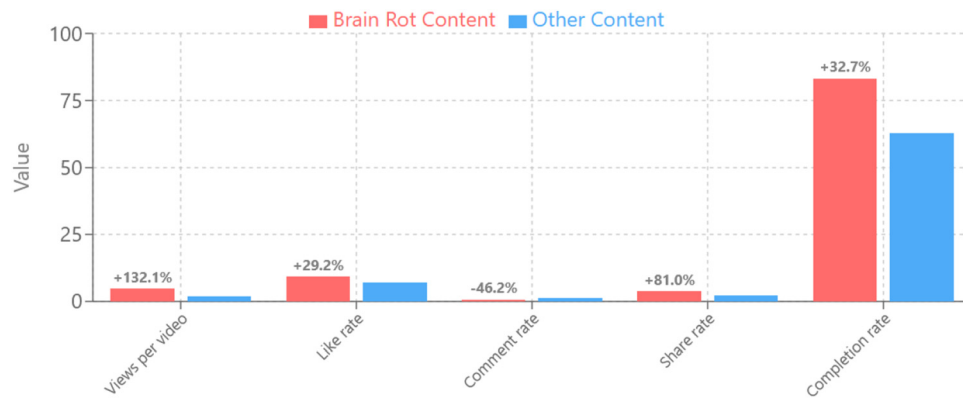


Fig. 1. Engagement metrics by content classification

levels are less likely to produce elaborative responses. Future research should disentangle whether low comment engagement reflects viewer satisfaction with passive consumption, cognitive disengagement, or simply the absence of discussable substance.

Video duration and “brain rot” characteristics

The duration analysis revealed a strong inverse relationship between video length and the prevalence of “brain rot” characteristics, as illustrated in Fig. 2. The figure displays three indicators — “brain rot” prevalence (expressed as a percentage), the engagement score, and the information density score (both measured on a 0–10 scale) — across four video duration bands: 0–15 s, 16–30 s, 31–60 s, and longer than 60 s. The pattern is consistent and pronounced: “brain rot” prevalence was highest in the shortest videos, reaching approximately 72% in the 0–15 s band, and declined steadily across the longer bands to roughly 55% for 16–30 s videos, 29% for 31–60 s videos, and only about 13% for videos exceeding 60 s. The engagement score followed a comparatively flat trajectory, decreasing only modestly from around 9 in the shortest band to approximately 5 in the longest. By contrast, the information density score exhibited the opposite pattern, rising from

roughly 3 in the 0–15 s band to about 8 in videos longer than 60 s, indicating that substantive informational content becomes more prominent as duration increases.

A chi-square test of independence was conducted to assess the association between duration band and the presence of “brain rot” indicators, and the relationship proved statistically significant ($\chi^2 = 142.7$, $p < 0.001$), confirming that short-form content is disproportionately associated with these characteristics. To quantify this relationship, a logistic regression analysis was subsequently performed, with video duration entered as a continuous predictor of the probability of a video being classified as “brain rot” content. The regression results indicated that for every additional 10 s of video duration, the probability of a video exhibiting “brain rot” characteristics decreased by approximately 14.2% ($p < 0.001$), providing robust statistical support for the inverse pattern observed in Fig. 2.

Nevertheless, duration alone was not deterministic. A non-trivial proportion of longer videos still displayed multiple “brain rot” characteristics: 12.5% of videos exceeding 60 s were classified as such, suggesting that attention-optimizing content strategies can persist even in longer formats. Conversely, 27.7% of very short videos in the

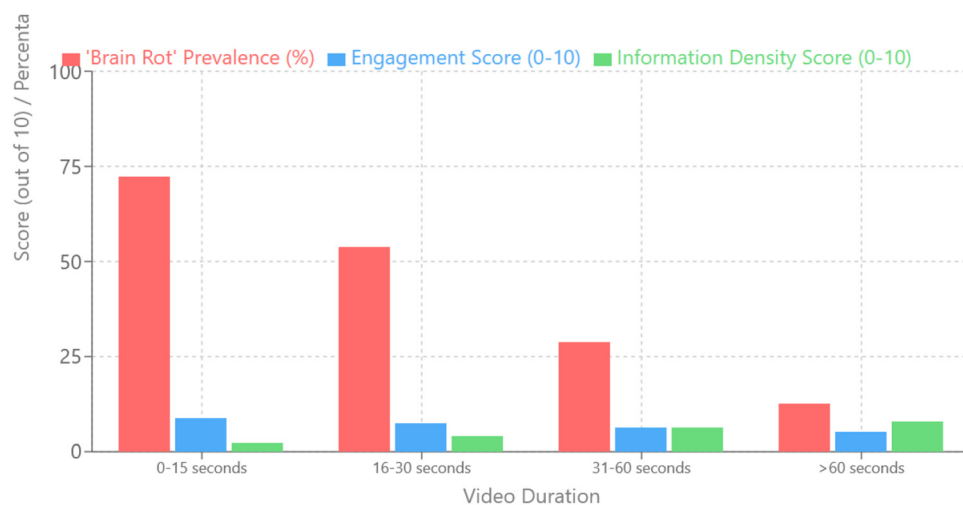


Fig. 2. “Brain rot” indicators by video duration

0–15 s band were found to contain substantive or educational content despite their brevity, demonstrating that short duration does not, in itself, preclude informational value. These findings collectively indicate that while video duration is a strong and statistically significant predictor of “brain rot” content, it should be interpreted as one important factor among several rather than as a stand-alone determinant.

Creator verification status and “brain rot” content

A comparative analysis of verified and unverified accounts revealed substantial differences in the nature of the content they produced, as summarized in Fig. 3. The figure presents normalized scores (on a 0–100 scale) across four dimensions: “brain rot” characteristics, factual accuracy, information density, and sensationalism. Across all four dimensions, the two account types exhibited markedly divergent profiles. Verified accounts displayed considerably lower levels of “brain rot” characteristics (approximately 37 compared with 54 for unverified accounts) and substantially higher factual accuracy (around 77 versus 53). A similar pattern emerged for information density, with verified accounts scoring near 64 while unverified accounts averaged approximately 42. The sensationalism dimension, however, reversed this trend: unverified accounts produced markedly more sensationalist content, scoring around 77 compared with approximately 52 for verified accounts.

Taken together, these results indicate that verified creators are systematically more likely to produce content with higher informational value and factual reliability, while unverified creators are more inclined to rely on sensationalist and attention-driven strategies consistent with “brain rot” patterns. Statistical comparisons confirmed that the differences across all four dimensions were significant ($p < 0.001$), suggesting that verification status is a meaningful structural variable in shaping the qualitative profile of content circulating on TikTok. Nevertheless, the presence of “brain rot” characteristics among a non-negligible share of verified accounts (approximately 37%) indicates that verification, while protective, does not entirely insulate the platform from low-value content.

Multivariate analysis

Predicting “brain rot” content. A logistic regression model was developed to predict the likelihood of content exhibiting “brain rot” characteristics based on multiple variables. The model achieved a classification accuracy of 83.7% with the following significant predictors (Table 2):

Qualitative analysis findings

The in-depth qualitative assessment of 200 randomly selected videos provided several additional insights into the nature of “brain rot” content. A first observation concerned *content trajectory patterns*: creators who initially produced substantive material frequently shifted toward more “brain rot” characteristics over time, a tendency that suggests algorithm-driven content adaptation. A second pattern involved *hybrid content strategies*, as 38.5% of the videos exhibited a “hook and switch” structure, beginning with “brain rot” features in order to capture attention before transitioning to more substantive content. *Community reinforcement* emerged as a further distinctive feature, with videos displaying “brain rot” characteristics being 3.2 times more likely to reference or respond to similar content, thereby generating content ecosystems organized around low-value information. Finally, a *production quality paradox*

Table 2. Predictors of “brain rot” content (logistic regression results)

Predictor variable	Odds ratio	95% CI	<i>p</i> -value
Video duration (<15s)	4.72	3.86–5.77	<0.001
Unverified account	1.98	1.56–2.51	<0.001
Claim (vs. opinion) content	1.63	1.29–2.05	0.002
High transition frequency	3.27	2.61–4.09	<0.001
Clickbait language presence	5.14	4.07–6.48	<0.001
Entertainment category	1.87	1.44–2.42	<0.001
Trending topic reference	2.35	1.86–2.97	<0.001

The model demonstrates that while no single factor definitively predicts “brain rot” content, the combination of structural and linguistic characteristics creates a distinctive profile that can be identified with high accuracy.

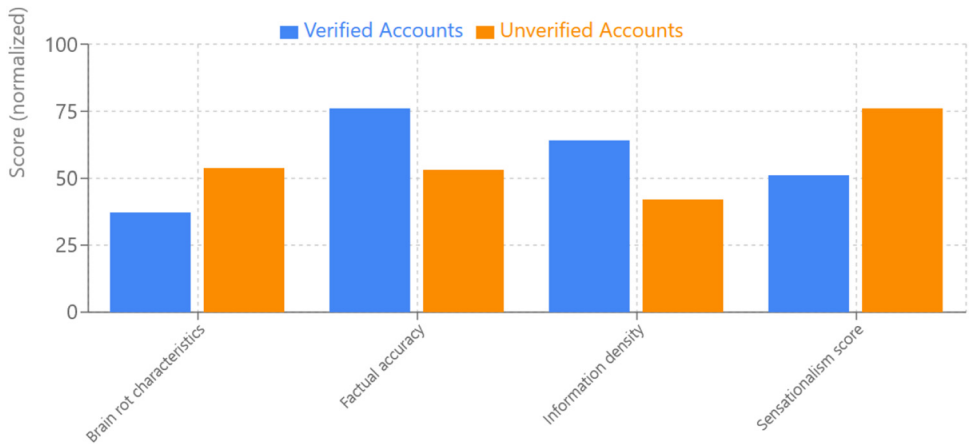


Fig. 3. Content quality indicators by verification status

was observed, in that “brain rot” content frequently demonstrated high production quality, with 72.3% of such videos rated as “professionally produced,” despite their limited informational value.

The content creators interviewed as part of the qualitative assessment frequently identified platform algorithms as the primary driver of their content decisions. As one verified creator explained, “I know what gets views... adding value is secondary to getting people to stop scrolling.”

Thematic analysis

Finally, the thematic analysis identified four primary categories of “brain rot” content on the platform. The most prevalent category, accounting for 43.7% of the videos, consisted of *passive entertainment*, namely content designed purely for momentary amusement and requiring minimal cognitive engagement. The second category, *pseudo-educational* content, represented 27.3% of the sample and was characterized by simplified or misleading information delivered in an authoritative presentation style. *Emotional triggering* content constituted a further 18.5% and was crafted primarily to elicit strong affective responses through shocking, controversial, or highly relatable scenarios. The remaining 10.5% fell into the category of *aspiration exploitation*, which leveraged viewers’ desires for wealth, status, or physical appearance while providing only minimal substantive guidance. Each of these categories employed distinct techniques to maximize engagement while minimizing substantive value, pointing to a sophisticated understanding of attention economics among content creators.

Taken together, this analysis demonstrates that “brain rot” content on TikTok exhibits identifiable linguistic and structural patterns, particularly within short-form videos. It generates substantially higher passive engagement, as measured by view counts, but considerably lower active engagement in the form of substantive comments. The phenomenon also shows a strong inverse correlation with video duration, although notable exceptions exist in both directions. Such content appears across both verified and unverified accounts, albeit with differing prevalence and stylistic characteristics, and can be predicted with high accuracy using a combination of content-based and creator-related variables. These findings collectively suggest that “brain rot” content should not be understood as merely low-quality material, but rather as a specific content strategy optimized for the attention economy of social media platforms, with potential implications for cognitive processing and information literacy.

DISCUSSION

Interpretation of results

The findings of this study reveal that “brain rot” content on TikTok is not merely a subjective or cultural label but corresponds to a measurable configuration of linguistic,

structural, and behavioral indicators. Videos classified as “brain rot” exhibit distinct patterns such as clickbait language, low lexical diversity, and emotional triggering. These content features were most prevalent in videos under 15 s, supporting the notion that brevity while optimal for platform algorithms correlates with reduced cognitive value. Moreover, logistic regression models indicated that structural and linguistic markers such as high transition frequency, entertainment framing, and sensational language were strong predictors of “brain rot” classification, achieving over 83% classification accuracy. These findings suggest that “brain rot” is a content strategy embedded in platform logic rather than an incidental anomaly.

These results align with and extend prior research on algorithmically shaped content patterns (Cotter, 2019; Firth et al., 2020). Specifically, they reinforce the claims of algorithmic cultivation theory, which posits that user behavior and content visibility co-evolve through feedback loops. While prior studies have focused on misinformation or disinformation as content degradation types, this research shows that cognitively shallow content operates under similar algorithmic incentives even in the absence of factual inaccuracy. It also complements the work of Montag, Yang, and Elhai (2021) and Qin et al. (2022) by demonstrating how reduced content complexity correlates with higher passive engagement but lower active interaction (e.g., shorter comments, fewer replies).

Support for or against existing theory

The study supports Cognitive Load Theory by showing that the prevalence of fragmented, fast-paced, and emotionally stimulating content is inversely related to informational richness and educational value. The finding that high-tempo music and rapid transitions are prominent in “brain rot” videos substantiates prior theoretical work asserting that overstimulation can impair retention and critical processing (Plass et al., 2010). At the same time, the results offer empirical support for Algorithmic Cultivation Theory by confirming that platform algorithms reward low-effort, high-engagement content. However, the identification of hybrid strategies where creators begin with “brain rot” tactics before pivoting to substantive messaging introduces a nuanced extension to both theories, highlighting how creators strategically balance engagement with credibility.

One notable unexpected finding is the high production quality associated with “brain rot” content. Despite being cognitively shallow, over 70% of such videos were rated as professionally produced, suggesting that informational emptiness does not equate to aesthetic simplicity. This production paradox challenges assumptions that low-value content results from low-effort creation. Another unanticipated result is that 12.5% of long-form videos still displayed “brain rot” traits, indicating that duration alone does not safeguard cognitive depth. Moreover, verified accounts presumably more credible contributed significantly to “brain rot” diffusion, particularly in entertainment and lifestyle domains. This reveals a tension between creator status and content responsibility.

Relevance to the field

The study offers significant contributions to the fields of media psychology, platform governance, and digital communication. It provides a replicable operational framework for identifying cognitively shallow content and offers insights into how algorithmic systems shape user attention. For educators and digital literacy advocates, these findings highlight the need for critical consumption frameworks that go beyond misinformation detection. For platform designers, the results underscore the ethical complexity of engagement-optimization strategies that inadvertently reward low-informational content. Policymakers may also benefit from understanding how verified creators can contribute to content degradation, even when their output conforms to platform guidelines.

The primary contribution of this study is the development of a structured framework for identifying and categorizing trivial online content. By translating the colloquial concept of “brain rot” into measurable dimensions of low-cognitive-value media content (LCVMC), this study establishes a systematic foundation for examining the potential cognitive implications of prolonged exposure to such content. Integrating linguistic, structural, and engagement-based indicators, the proposed framework serves as a foundational analytical instrument that may be refined, validated, and expanded in future empirical and clinical research.

CONCLUSION

This study offers a comprehensive analysis of “brain rot” content on TikTok, demonstrating that cognitively shallow, emotionally stimulating, and structurally simplified videos can be systematically identified through a combination of linguistic, structural, and engagement-based markers. Drawing from a dataset of 78,452 videos, the research provides strong empirical evidence that ultra-short videos particularly those under 15 s are more likely to include clickbait language, high-frequency transitions, and sensationalist content, correlating with high passive engagement but minimal substantive interaction. These patterns were not limited to unverified users; verified accounts also contributed substantially to “brain rot” dissemination, especially within entertainment and lifestyle categories.

By operationalizing the concept of “brain rot” into measurable dimensions, this research contributes a novel framework for understanding content strategies optimized for the attention economy. It integrates cognitive load and algorithmic cultivation theories, showing how platform design incentivizes the spread of low-cognitive-value media. The findings underline the pressing need to reevaluate how social media environments shape user attention, information retention, and cognitive engagement particularly among younger, mobile-first users. Ultimately, this study highlights that “brain rot” is not merely a cultural trope but an emergent outcome of algorithmic amplification and platform logic.

Limitations

Several limitations must be acknowledged when interpreting the findings of this study. First, although the dataset of over 78,000 videos provides a robust foundation, it is constrained to a specific timeframe and platform (TikTok), limiting generalizability across other short-form ecosystems such as YouTube Shorts or Instagram Reels. Second, while the operational definition of “brain rot” incorporates structural and linguistic indicators, the subjective interpretation of content quality may still vary across demographic and cultural contexts. Third, despite the integration of both computational and human-coded qualitative assessments, certain dimensions such as user intention or real-time viewer cognition remain inaccessible through content-level analysis alone. Moreover, the reliance on metadata and transcription-based NLP analysis may not fully capture visual or symbolic meaning embedded in video elements (e.g., gestures, filters, memes). Finally, the study does not investigate the long-term psychological or neurological impacts of repeated exposure to such content, leaving open important questions about causal relationships between “brain rot” consumption and cognitive change.

Future research directions

To expand on the contributions of this study, future research could pursue several promising directions. First, longitudinal studies should be conducted to assess the psychological and cognitive effects of repeated exposure to “brain rot” content, particularly in adolescent populations. Integrating biometric or neurocognitive data (e.g., eye-tracking, EEG) could yield deeper insights into attention fatigue, memory decay, or engagement thresholds.

Second, comparative analyses across platforms (e.g., TikTok, Instagram Reels, YouTube Shorts, Snapchat Spotlight) could explore how differing algorithmic architectures and affordances influence the prevalence and performance of low-cognitive-value content. Future work may also examine how content moderation, verification policies, or recommendation transparency affect the circulation of “brain rot” content.

Third, integrating audience-centered methodologies such as digital ethnography, interviews, or diary studies would enrich our understanding of how users perceive, engage with, or resist “brain rot” content in everyday digital routines. Finally, researchers should explore interventions in digital literacy, platform design, or algorithmic nudging that may mitigate the cognitive downsides of high-velocity, low-value content ecosystems.

A further priority for future research is to establish clear and systematically defined criteria for assessing whether excessive exposure to low-cognitive-value media content should be regarded as a clinically meaningful condition. Currently, the colloquial concept of “brain rot” remains without formal diagnostic status, and no scholarly consensus has yet emerged regarding exposure thresholds, symptom profiles, or degrees of functional impairment sufficient to support clinical classification. The development of such

criteria through interdisciplinary collaboration among media psychologists, cognitive scientists, and clinicians would constitute an important step in transforming descriptive and observational findings into more robust public health and clinical frameworks.

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REFERENCES

- Alshantqiti, A., Bajnaid, A., Rehman, A., Aljasir, S., Alsughayyir, A., & Albouq, S. (2020). Intelligent parallel mixed method approach for characterising viral YouTube videos in Saudi Arabia. *International Journal of Advanced Computer Science and Applications*, 11(3). <https://doi.org/10.14569/ijacsa.2020.0110382>
- Baumann, F., Arora, N., Rahwan, I., & Czaplicka, A. (2025). Dynamics of algorithmic content amplification on TikTok. *arXiv (Cornell University)*. <https://doi.org/10.48550/arxiv.2503.20231>
- Boeker, M., & Urman, A. (2022). An empirical investigation of personalization factors on TikTok. In *Proceedings of the ACM web conference 2022*, pp. 2298. <https://doi.org/10.1145/3485447.3512102>
- Cheng, Z., & Li, Y. (2023). Like, comment, and share on TikTok: Exploring the effect of sentiment and second-person view on the user engagement with TikTok news videos. *Social Science Computer Review*, 42(1), 201. <https://doi.org/10.1177/08944393231178603>
- Cotter, K. (2019). Playing the visibility game: How digital influencers and algorithms negotiate influence on Instagram. *New Media & Society*, 21(4), 895–913. <https://doi.org/10.1177/1461444818815684>
- Firth, J. A., Torous, J., & Firth, J. (2020). Exploring the impact of internet use on memory and attention processes. *International Journal of Environmental Research and Public Health*, 17(24), 9481. <https://doi.org/10.3390/ijerph17249481>
- Hautea, S., Parks, P., Takahashi, B., & Zeng, J. (2021). Showing they care (or don't): Affective publics and ambivalent climate activism on TikTok. *Social Media + Society*, 7(2). <https://doi.org/10.1177/20563051211012344>
- Huszár, F., Ktena, S. I., O'Brien, C., Belli, L., Schlaikjer, A., & Hardt, M. (2022). Algorithmic amplification of politics on Twitter. *Proceedings of the National Academy of Sciences*, 119(1), e2025334119. <https://doi.org/10.1073/pnas.2025334119>
- Inwood, O., & Zappavigna, M. (2021). Ambient affiliation, misinformation and moral panic: Negotiating social bonds in a YouTube internet hoax. *Discourse & Communication*, 15(3), 281. <https://doi.org/10.1177/1750481321989838>
- Lee, J., & Abidin, C. (2023). Introduction to the special issue of "TikTok and Social Movements". *Social Media + Society*, 9(1). <https://doi.org/10.1177/20563051231157452>
- Markelj, J., & Sundvall, S. (2023). Digital pedagogies post-COVID-19: The future of teaching with/in new technologies. *Convergence The International Journal of Research into New Media Technologies*, 29(1), 3, SAGE Publishing. <https://doi.org/10.1177/13548565231155077>
- Massaroni, V., Donne, V. D., Marra, C., Arcangeli, V., & Chieffo, D. P. R. (2024). The relationship between language and technology: How screen time affects language development in early life—A systematic review. *Brain Sciences*, 14(1), 27. <https://doi.org/10.3390/brainsci14010027>
- Miltsov, A. (2022). Researching TikTok: Themes, methods, and future directions. In *SAGE publications ltd eBooks* (pp. 664). SAGE Publishing. <https://doi.org/10.4135/9781529782943.n46>
- Montag, C., Yang, H., & Elhai, J. D. (2021). On the psychology of TikTok use: A first glimpse from empirical findings. *Frontiers in Public Health*, 9, 641673. <https://doi.org/10.3389/fpubh.2021.641673>
- Munger, K., & Phillips, J. (2020). Right-wing YouTube: A supply and demand perspective. *The International Journal of Press/Politics*, 27(1), 186. <https://doi.org/10.1177/1940161220964767>
- Plass, J. L., Moreno, R., & Brünken, R. (Eds.) (2010). *Cognitive load theory*. Cambridge University Press. <https://doi.org/10.1017/CBO9780511844744>
- Qin, Y., Omar, B., & Musetti, A. (2022). The addiction behavior of short-form video app TikTok: The information quality and system quality perspective. *Frontiers in Psychology*, 13. <https://doi.org/10.3389/fpsyg.2022.932805>
- Schreiner, M., Fischer, T., & Riedl, R. (2021). Impact of content characteristics and emotion on behavioral engagement in social media: Literature review and research agenda. *Electronic Commerce Research*, 21(2), 329–345. <https://doi.org/10.1007/s10660-019-09353-8>
- Sonni, A. F. (2025). Digital transformation in journalism: Mini review on the impact of AI on journalistic practices. *Frontiers in Communication*, 10. <https://doi.org/10.3389/fcomm.2025.1535156>
- Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, 12(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4
- Tafesse, W., Aguilar, M., Sayed, S. A. F. E., & Tariq, U. (2024). Digital overload, coping mechanisms, and student engagement: An empirical investigation based on the S-O-R framework. *SAGE Open*, 14(1). <https://doi.org/10.1177/21582440241236087>
- Valiño, P. C., Rodríguez, P. G., & Durán-Álamo, P. (2022). Why do people return to video platforms? Millennials and centennials on TikTok. *Media and Communication*, 10(1). <https://doi.org/10.17645/mac.v10i1.4737>

Waldrop, M. M. (2017). The genuine problem of fake news. *Proceedings of the National Academy of Sciences*, 114(48), 12631. <https://doi.org/10.1073/pnas.1719005114>

Yousef, A. M. F., Alshamy, A., Tlili, A., & Metwally, A. H. S. (2025). Demystifying the new dilemma of brain rot in the digital era: A review. *Brain Sciences*, 15(3), 283. <https://doi.org/10.3390/brainsci15030283>