Jump Cut Editing Style and Transition Frequency Differentially Affect Interactive and Sustained Engagement in Short-Form Video

Authors

Florian Dost – Professor of Marketing – Brandenburg University of Technology – Erich-Weinert-Str. 1, 03046 Cottbus, Germany – Email: florian.dost@b-tu.de

Yujing Huang – MSc of Business Administration – Brandenburg University of Technology – Erich-Weinert-Str. 1, 03046 Cottbus, Germany – Email: huangyujing9002@gmail.com

Abstract

Short-form video captures Marketers' attention, yet evidence on how editing shapes engagement is limited. We test how two jump-cut styles (seamless vs overlapping) and transition frequency (low/medium/high) influence two outcomes: interactive engagement (liking) and sustained engagement (completion/rewatch). After a field benchmark to set actionable pace levels, we ran a between-subjects 2×3 experiment plus an unedited control (N=242) using seven variants of the same 20-second talking-head clip. Seamless cuts increased liking relative to overlapping and unedited; overlapping cuts increased sustained engagement, but this advantage attenuated as transition frequency rose. Higher pacing reduced sustained engagement overall. Theoretically, results map editing styles onto distinct engagement routes: processing fluency aligns with likes, while micro-disruption supports attention. Managerially, editors should match cut to KPI: prefer seamless at moderate pace to drive likes; use overlapping at low pace to improve completion; avoid chasing speed for its own sake.

Keywords: jump-cut style; short-form video engagement; TikTok

Suggested Tracks: Digital Marketing

Introduction

Short-form video is now central to social media marketing, yet evidence-based guidance on editing remains scarce. One editing device, the "jump cut", has migrated from film to talking-head shorts, where creators use it to compress speech and pace delivery (Liu et al., 2018; McMullan, 2021). Despite its prevalence (and tooling that automates it), we know little about how styles of jump cuts and their frequency shape outcomes marketers care about. Engagement, moreover, is not only what audiences do (e.g., like) but also whether they keep watching (Berger et al., 2023; TikTok, 2025).

This paper isolates two jump-cut styles widely observed in practice: 1) seamless cuts (tightening by removing silence while preserving continuity) and 2) overlapping cuts (introducing slight audio overlaps that create track disruptions). The paper examines how transition frequency (low/medium/high) conditions their effects. Grounded in processing fluency theory (Reber et al., 2004) and the asymmetric sampling in time model of speech perception (Poeppel, 2003), we predict a dual-route account of engagement: fluency should elevate affective responses (likes), while controlled, prediction-error-inducing disruptions can help sustain attention over time. Beyond a minimum frequency, seamless cuts should improve fluency, while overlapping cuts should elevate sustained attention, but only when used in moderation.

We contribute in three ways. First, a field benchmark of real-world cut rates from 50 best-practice TikToks to define actionable low/medium/high transition levels. Second, a 2×3 online experiment with an additional unedited control that tests how cut style × frequency jointly shape (i) interactive engagement (liking) and (ii) sustained engagement (completion/rewatch). Third, clear managerial guidance translating effects into editing rules of thumb. Anticipating the results previewed later, seamless cuts increase liking, overlapping cuts better sustain attention, and higher transition frequency is relevant in both types of effect: seamless cuts improve engagement only beyond a minimum frequency, but overlapping cuts elevate sustained attention only when used in moderation. These results imply different edits for different goals and a ceiling to "more, faster" pacing (Liu et al., 2018; Stuppy et al., 2024). Together, the findings connect editing micro-choices to measurable marketing impact and offer creators simple, testable heuristics for short-form production.

Background: editing for engagement

Jump cuts—once a film device—now proliferate in talking-head shorts as an audio-first pacing tool. We focus on two styles seen in practice: seamless (remove pauses/errors; preserve continuity) and overlapping (slight audio overlaps that intentionally break continuity). These edits are deployed at different transition frequencies (from between every word, between sentences, to only removing longer pauses). In a medium that values brevity, jump cuts further shorten the content; but jump cuts also target audience engagement.

Platforms reward not only what people do (likes) but whether they keep watching; accordingly, we distinguish interactive engagement (liking) from sustained engagement (completion/rewatch) (Berger et al., 2023; TikTok, 2025). In the later experiment, both outcomes are measured as engagement likelihood: likelihood to like (interactive) and likelihood to complete/rewatch (sustained), following validated two-item scales (Berger et al., 2023; Chen et al., 2025; Wies et al., 2023).

Theory and Hypotheses

Processing fluency. Processing fluency theory holds that the easier a stimulus is to process, the more positive the affect it elicits, which is often expressed as liking the content

(Reber et al., 2004; Winkielman & Cacioppo, 2001). Seamless jump cuts should heighten perceptual/conceptual fluency by tightening pacing while retaining natural micro-gaps and onsets; overlapping cuts inject micro-disruptions that reduce fluency; unedited clips keep redundancies that depress fluency (Liu et al., 2018). Thus, fluency should map onto interactive responses.

Prediction error and AST. Sustained attention is well explained by predictive-coding accounts: when incoming cues violate expectations, the brain issues prediction-error signals that (bottom-up) capture attention (Armeni et al., 2019). The Asymmetric Sampling in Time (AST) model specifies two temporal windows for speech—short (~20–40 ms) and long (~150–250 ms); disruptions that misalign with these windows raise processing demands (Poeppel, 2003). Overlapping cuts, by clipping onsets and erasing micro-pauses, are more likely to violate both windows, prompting repeated prediction updates; seamless cuts, respecting both windows, should trigger fewer errors. Hence, prediction error should map onto sustained attention.

Transition frequency as moderator. Editing pace consumes limited processing capacity (Lang, 2000): each additional cut taxes resources before semantic processing. When frequency is low, style differences matter but remain manageable; as frequency rises, cumulative mismatches from overlapping cuts can push viewers toward overload, reducing their attentional edge; conversely, when transition frequency is too low, the changes in pacing and fluency may not matter for outcomes.

Figure 1 shows the conceptual model. Formally, we hypothesize:

- **Hypothesis H1** (Fluency → interactive engagement). Seamless jump cuts generate higher interactive engagement (likes) than overlapping jump cuts, or unedited videos.
- **Hypothesis H2** (Prediction error → sustained engagement). Overlapping jump cuts generate higher sustained engagement (continued watching/rewatch) than seamless jump cuts, and unedited video.
- **Hypothesis H3a** (Pace × style on interactive). Transition frequency accentuates the positive effect of seamless cuts on likes; the seamless–overlapping/baseline gap exists beyond a minimum threshold at medium to high frequency.
- **Hypothesis H3b** (Pace × style on sustained). Transition frequency attenuates the positive effect of overlapping cuts on continued watching; the gap gets smaller beyond a maximum frequency.

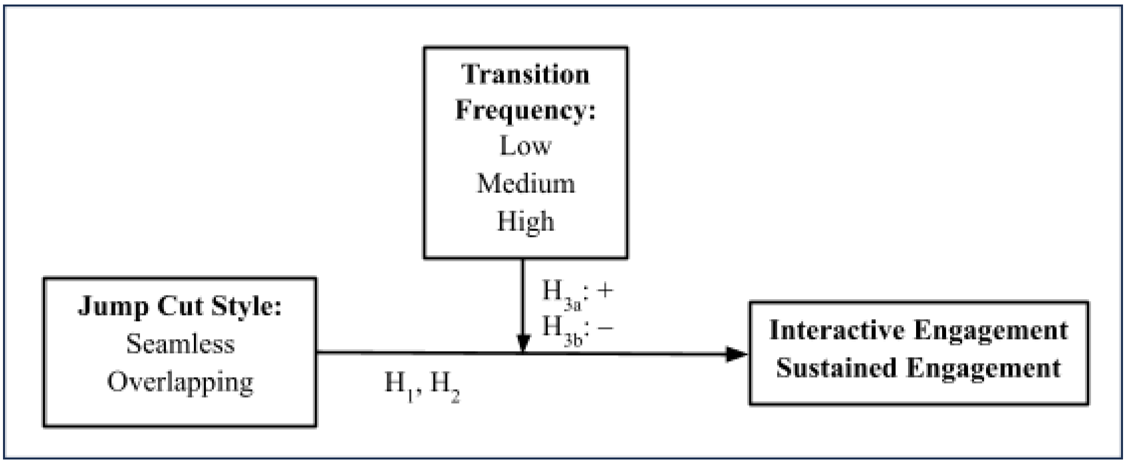

Figure 1: Conceptual Model

Study 1 (pre-study): field benchmark for transition frequency

To calibrate actionable low/medium/high cut rates, we scraped 50 high-performing, informative talking-head TikToks (from a list of most successful German TikTok influencers/accounts) and auto-detected scene boundaries with PySceneDetect. The distribution yielded a mean of 0.37 cuts/s (SD = 0.17; range = 0.13–0.82). Using the 16th/50th/84th percentiles produced three benchmarks: 0.189, 0.331, and 0.517 cuts/s (low/median/high), which informed the main experiment's manipulations.

Study 2: main experiment (2 × 3 + control)

Design & stimuli. A between-subjects 2 (jump-cut style: seamless vs. overlapping) × 3 (transition frequency: low/medium/high) plus an unedited control yielded seven random groups. Stimuli were seven versions of the same ~20-second educational talking-head video (source: a best-performing post from a German university's marketing account). All versions were produced in CapCut with identical visuals and bilingual subtitles; only cut style and pace varied. Participants were required to watch with sound on.

Participants & procedure. A convenience sample (students on campus + acquaintances via social media) completed the study on Google Forms. After a short-form video usage screener, participants were randomly assigned to one of the seven conditions, watched the clip as if encountered in a feed, and passed a factual attention check. N = 251 started; after nine attention-check failures, N = 242 remained (attrition 3.6%). Demographics of the sample were age M = 29.88 (SD = 4.11), 53.7% female / 43.8% male / 2.1% diverse. A power analysis targeted N ≈ 244 (≥80% power for medium effects across 7 groups).

Measures were:

- Interactive engagement likelihood (IE): two 7-point items (e.g., "likelihood to like/positively react"), averaged.
- Sustained engagement likelihood (SE): two 7-point items (e.g., "let similar videos play through / watch again"), averaged.
- Manipulation checks: style ("edits felt smooth → abrupt") and pace ("very slow → very fast").
- Covariates: subtitle usefulness, perceived future orientation of speech, and content relevance.

Reliability was good for interactive engagement and sustained engagement (alphas > .85); CFA supported discriminant validity. Manipulation checks showed ordered separation across pace levels (low < medium < high) and differences across cut style.

Analysis plan. Hypotheses were tested in a multiple-regression framework with six experimental group dummies (all testing against unedited control). All analyses were conducted in the R software.

Results

Table 1 depicts estimates from both models, model 1 shows the estimated group differences against unedited video on interactive engagement, model 2 the estimates on sustained engagement.

As predicted, we find that seamless cuts can significantly increase interactive engagement, but overlapping cuts cannot, in line with a fluency account of engagement (H1). Conversely, overlapping cuts can improve sustained engagement, but seamless cuts cannot, in line with an AST account of engagement (H2). Further, Figure 2 shows respective group means and reveals moderation effects of both accounts with transition frequency.

Table 1: Model Summary

	Model 1 – interactive	Model 2 – sustained
(Intercept)	**3.171****** **(0.223)**	**2.471****** **(0.222)**
SeamlessCut_Low	0.358 (0.318)	-0.383 (0.316)
SeamlessCut_Med	**0.829****** **(0.315)**	0.014 (0.314)
SeamlessCut_High	**0.843****** **(0.315)**	-0.257 (0.314)
OverlappingCut_Low	-0.363 (0.318)	**1.396****** **(0.316)**
OverlappingCut_Med	-0.333 (0.318)	**1.602****** **(0.316)**
OverlappingCut_High	-0.271 (0.315)	0.329 (0.314)
N	242	242
F	5.580	12.549
R^2	0.125	0.243

Notes. Significant estimates ($p < 0.05$) marked in bold. SE in parentheses.

Specifically, seamless cuts improve interactive engagement only for the groups with medium or high transition frequency (corresponding to the median and 84% quantiles in the TikTok pre-study), but not significantly for rare transitions (see Figure 2, left panel). This finding corresponds with a minimum threshold for seamless cuts to improve continuity and thus fluent perception (H3a). Overlapping cuts seem to show a different pattern (Figure 2, right panel): here, a medium frequency slightly improves mean sustained engagement over low frequency, but then that advantage erodes for the high frequency group, suggesting an (optimal) maximum level for gaining attention from disturbed continuity predictions (H3b).

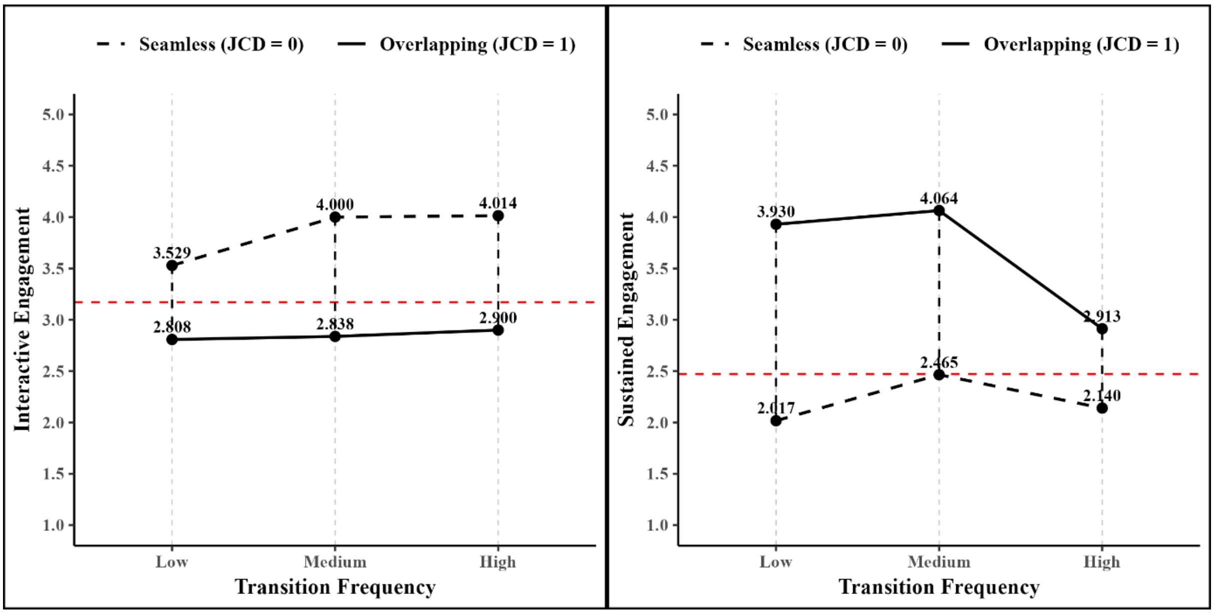

Figure 2: Group Means on Different Types of Engagement

Discussion

Editing micro-choices measurably shape distinct engagement outcomes in short-form videos. Seamless cuts, which may raise processing fluency, consistently increased interactive engagement (liking). Overlapping cuts, which may inject small prediction errors, boosted sustained engagement (keep watching/rewatch), but this edge shrinks at higher transition frequency. In short: there is no single "best" jump cut; optimal editing is goal-contingent and pace-bounded.

Implications for theory. First, we tie editing style to engagement types: fluency aligns with affective, low-effort responses (likes), while micro-disruption aligns with attentional maintenance. Second, we specify transition frequency as both a perceptual and a capacity moderator: as edits accumulate, their benefits for fluency starts only after crossing a minimal threshold, but benefits for attention attenuate, clarifying why "more, faster" plateaus and then declines. Third, we operationalize engagement as two routes—interactive vs. sustained—showing they can diverge within the same stimulus, advancing work that has tended to collapse them.

Managerial takeaways.

- To optimize for likes: prefer seamless cuts at medium pace; avoid over-accelerating.
- Optimize for completion/rewatch: use overlapping cuts at low pace. If you must speed up, dial back the overlap.
- Don't chase speed for its own sake: high pacing taxes attention and narrows the overlapping advantage.
- Match edit to KPI: publish two versions when goals differ (IE vs. SE); A/B test the style at low–medium pace bands.
- Guardrails: anchor pace near real-world medians, not the extremes; ensure content relevance, which consistently helps both outcomes.

Limitations & future work. The sample is convenience-based and the stimuli are single-topic/format; replication with varied genres, lengths, and platforms, plus behavioral measures (true likes, watch-through) is warranted. Future studies could compare alternative disruption types (e.g., hard visual cuts, sound design), test creator/brand moderations, and probe non-linear pacing ceilings with finer granularity.

Conclusion. Editing style and pace are actual leverages for engagement on social media. Use seamless to earn likes; use overlapping at low pace to keep viewers. Above all, choose the cut for the outcome, and resist the myth that faster is always better.

References

Armeni, K., Willems, R. M., van den Bosch, A., & Schoffelen, J.-M. (2019). Frequency-specific brain dynamics related to prediction during language comprehension. *NeuroImage*, *198*, 283–295. https://doi.org/10.1016/j.neuroimage.2019.04.083

Berger, J., Moe, W. W., & Schweidel, D. A. (2023). What Holds Attention? Linguistic Drivers of Engagement. *Journal of Marketing*, *87*(5), 793–809. https://doi.org/10.1177/00222429231152880

Chen, H., Wang, P., & Hao, S. (2025). AI in the spotlight: The impact of artificial intelligence disclosure on user engagement in short-form videos. *Computers in Human Behavior*, *162*, 108448. https://doi.org/10.1016/j.chb.2024.108448

Lang, A. (2000). The Limited Capacity Model of Mediated Message Processing. *Journal of Communication*, *50*(1), 46–70. https://doi.org/10.1111/j.1460-2466.2000.tb02833.x

Liu, X., Shi, S. W., Teixeira, T., & Wedel, M. (2018). Video Content Marketing: The Making of Clips. *Journal of Marketing*, *82*(4), 86–101. https://doi.org/10.1509/jm.16.0048

McMullan, J. (2021). The great jump cut (r)evolution: A case for studying the evolution of vlogging production techniques. *First Monday*. https://doi.org/10.5210/fm.v26i2.10547

Poeppel, D. (2003). The analysis of speech in different temporal integration windows: Cerebral lateralization as 'asymmetric sampling in time.' *Speech Communication*, *41*(1), 245–255. https://doi.org/10.1016/S0167-6393(02)00107-3

Reber, R., Schwarz, N., & Winkielman, P. (2004). Processing Fluency and Aesthetic Pleasure: Is Beauty in the Perceiver's Processing Experience? *Personality and Social Psychology Review*, *8*(4), 364–382. https://doi.org/10.1207/s15327957pspr0804_3

Stuppy, A., Landwehr, J. R., & McGraw, A. P. (2024). The Art of Slowness: Slow Motion Enhances Consumer Evaluations by Increasing Processing Fluency. *Journal of Marketing Research*, *61*(2), 185–203. https://doi.org/10.1177/00222437231179187

TikTok. (2025). *TikTok Creator Academy: Empowering Creators to Grow and Succeed on TikTok | TikTok For Creator*. https://www.tiktok.com/creator-academy/en/article/tool-analytics-intro

Wies, S., Bleier, A., & Edeling, A. (2023). Finding Goldilocks Influencers: How Follower Count Drives Social Media Engagement. *Journal of Marketing*, *87*(3), 383–405. https://doi.org/10.1177/00222429221125131

Winkielman, P., & Cacioppo, J. T. (2001). Mind at ease puts a smile on the face: Psychophysiological evidence that processing facilitation elicits positive affect. *Journal of Personality and Social Psychology*, *81*(6), 989.