

Research Article

An Experimental Study of Human and Artificial Intelligence Collaboration in TikTok Advertising: Effects on Audience Perception and Engagement

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ABSTRACT

The use of generative artificial intelligence, or GenAI in short form video advertising, continues to grow due to its efficiency and scalability. However, questions remain regarding audience acceptance, perceived authenticity, and the effectiveness of AI-generated advertising on social media platforms such as TikTok. This study examines how different creative configurations, namely Human Only, AI Only, and Human-AI Collaboration, influence audience perception and engagement in TikTok advertising. This study employed an experimental mixed methods approach. Quantitatively, two sequential A/B split tests were conducted using TikTok Ads Manager to compare Human Only versus AI Only advertising and Human Only versus Human-AI Collaboration advertising. Audience engagement was measured using Completion Rate as the primary indicator and six-second view rate as a secondary indicator. Qualitatively, in-depth interviews with active TikTok users were conducted to examine audience processing mechanisms based on the Elaboration Likelihood Model. The results show that Human Only advertising achieved higher completion rates and early engagement than AI Only advertising. Furthermore, Human-AI Collaboration generated the highest engagement compared to Human-Only advertising. Qualitative findings indicate that human involvement strengthens perceived authenticity and trust, while AI supports visual structure that sustains attention and message elaboration. In conclusion, Human-AI Collaboration represents the most effective and socially acceptable approach to short-form video advertising, with implications for digital advertising strategy, ethical AI use, and the sustainable integration of generative technologies in social media communication.

Keywords: Artificial Intelligence Generated Content (AIGC); Completion Rate; Elaboration Likelihood Model; Generative AI; Mixed-Methods; Human-AI Collaboration; TikTok Advertising

1. INTRODUCTION

The digital advertising industry is undergoing a major transformation driven by the need for content that is fast, relevant, and engaging, especially on social media platforms (Faruk et al., 2021; Sholih & Almas Ashar, 2025). A key driver is Generative AI (Gen AI), an evolution beyond rule-based systems (Narrow AI) toward models that can creatively produce new content from large-scale data (Russell & Norvig, 2021; Dwivedi et al., 2023).

Gen AI is now widely adopted by global brands such as Cadbury, Coca-Cola, Microsoft, McDonald's, and Samsung (AdWeek, 2024; Forbes, 2024), because it can accelerate production, reduce costs, and generate high-quality content (Kang & Lou, 2022; Hartmann et al., 2025). The technology is reshaping not only content creation but also consumer interactions and decision-making processes (Grewal et al., 2025; Mogaji & Jain, 2024). This aligns with broader evidence that digital transformation technologies reshape online and social marketing practice (Dyah Kusumastuti et al., 2025). Industry leaders recognize the scale of this shift, with 70% of CEOs believing Gen AI will significantly change their businesses within the next three years (PwC, 2024).

Despite its promise, large-scale adoption of Gen AI brings challenges. AI-generated advertising frequently raises ethical concerns and questions about audience acceptance (Wu & Wen, 2021). Projections indicate that AI could replace more than 200,000 jobs within the next 3 to 5 years (Bloomberg, as cited by Exploding Topics, 2025) and prompt about 14% of the global workforce approximately 375 million people to switch careers by 2030 (McKinsey, as cited by Exploding Topics, 2025). These concerns create tension between human creators and Gen AI (Anantrasirichai & Bull, 2022) and fuel AI Anxiety, a fear that human creativity will be displaced. Studies report that 36% of respondents experience this anxiety, more than 40% of consumers have lower trust in AI-based ads (Haupt et al., 2025; Kim et al., 2025), and 52% of young people aged 18 to 24 worry about its impact on their career prospects (BMG, as cited by Exploding Topics, 2024).

In practice, two dominant approaches are used to produce Gen AI advertising content: (1) AI-Only (pure AIGC), in which the entire creative process and core assets are automatically generated by AI while humans provide minimal intervention such as initial prompting or basic post-production like cut-to-cut editing, and (2) Human–AI Collaboration, in which AI acts as a creative assistant that augments rather than replaces human creators (Gao et al., 2023; Haupt et al., 2025; Zhang et al., 2022; Sowa & Przegalinska, 2025). The collaborative approach is generally seen as more acceptable because it preserves message credibility (Baek et al., 2024; Haupt et al., 2025). Even so, challenges remain. For example, transparency about content provenance can lower audience preference even when human involvement is present (Lefkeli et al., 2024).

Despite the ongoing debate and these challenges, a significant gap persists in the academic literature. Mogaji & Jain (2024) underscore the need for continued research on consumer behavior in the Gen AI era. Prior studies have focused heavily on text-based or static visual content, while empirical work on Gen AI in short-form video advertising remains limited (Kang & Lou, 2022; Chung et al., 2025). Madathil (2025) compared AI-Only and Human–AI Collaboration using a multi-method approach, although the focus was on YouTube. This leaves a gap on TikTok, a platform with a distinctive engagement algorithm. This study addresses the gap through a mixed-methods approach grounded in the Elaboration Likelihood Model (ELM) (Cacioppo et al., 1986; Petty et al., 1983). ELM posits two routes to attitude formation. The central route relies on deep cognitive processing of argument quality. The peripheral route relies on affective cues.

In this study, the quantitative experiment focuses on Completion rate as the primary metric and 6-second view rate as a secondary metric. Other indicators, such as likes, comments, and CTR, are recorded as exploratory due to their low frequencies. Qualitative *in-depth interviews* are then conducted to probe participants’ cognitive and emotional processes. Together, these methods aim to contribute a unique perspective by offering early, indicative causal evidence on how the two Gen AI approaches affect audience engagement and perceptions in short-form video advertising.

Research Questions

- RQ1: Are there significant differences in audience engagement metrics across AI-Only, Human–AI Collaboration, and Human-Only content?
- RQ2: How do audiences process the persuasive messages in these ads via ELM’s central route (argument quality) and peripheral route (emotional cues)?

Theoretically, this study extends the literature on the collaborative role of humans in the Gen AI era, particularly for short-form video marketing strategies. Practically, the findings can guide marketers, creators, and brands to leverage AI strategically without losing emotional connection and human value. The results can also inform policies for ethical, effective, and audience-oriented content production.

2. RESEARCH METHOD

2.1 Study Design

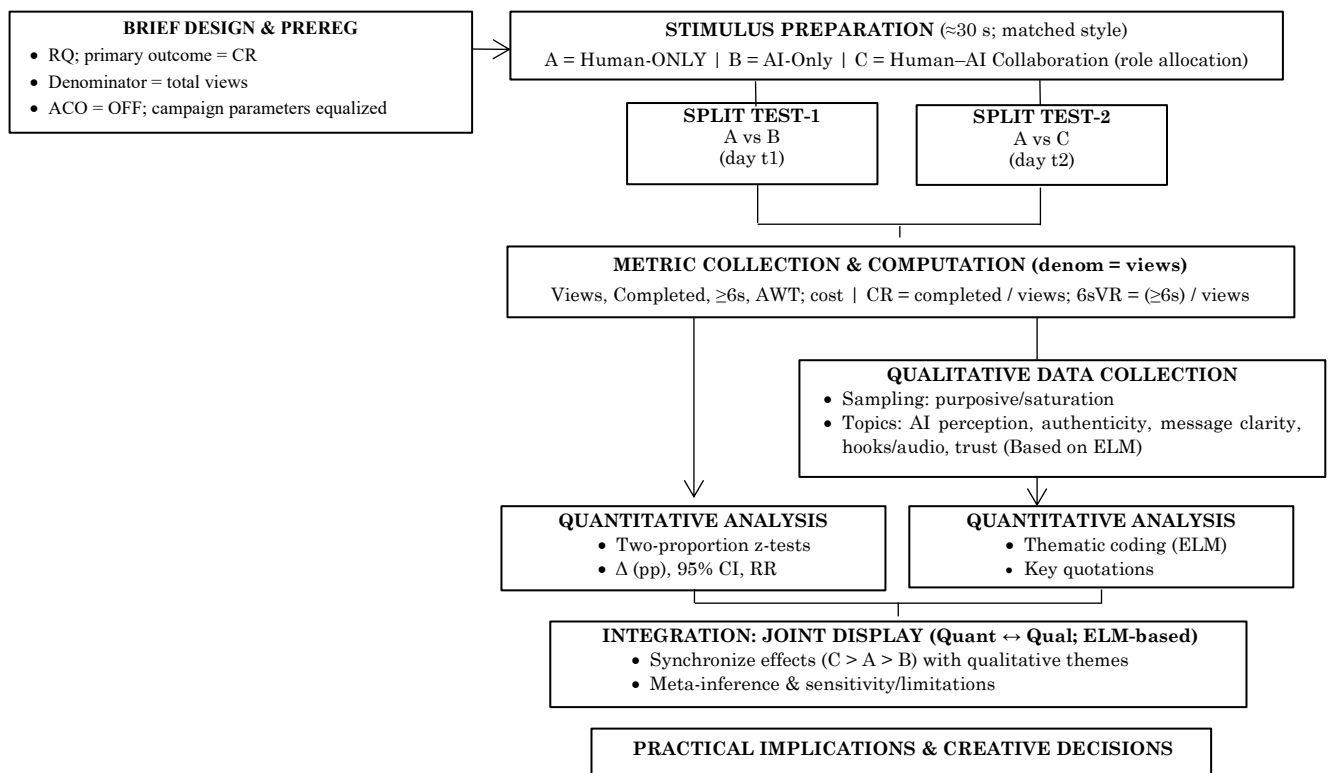


Figure 1. Research framework. Study flow from stimulus setup (A: Human-Only, B: AI-Only, C: Human–AI Collaboration), two sequential split tests (A vs B, A vs C), metric collection (Completion rate, 6-second view rate, Average watch time, cost), quantitative and qualitative analyses, and integration at the interpretation stage.

This research adopts a mixed-methods sequential explanatory design, in which qualitative interviews follow a quantitative experiment to explain the mechanisms behind the quantitative findings (Creswell & Creswell, 2023). The design was chosen to combine causal effect estimation from the experiment with the explanatory depth of qualitative inquiry and to generate more comprehensive meta-inferences (Younas et al., 2025). The Elaboration Likelihood Model (ELM) framework guides the operationalization of audience engagement, distinguishing central and peripheral routes, as well as cross-stage interpretation (Cacioppo et al., 1986). For reader clarity, **Figure 1** summarizes the study flow, metric collection, and analytic integration used in this work.

2.2 Phase 1: Quantitative Experiment

Platform and design

The experiment used a sequential split A/B test on TikTok Ads Manager, which by default randomizes audiences into two arms while holding campaign variables constant. This approach is commonly used to test ad effectiveness on social media (TikTok, 2025; Braun & Schwartz, 2025). Because the platform can compare only two ads at a time, two sequential split tests were conducted: (1) Human-Only vs AI-Only and (2) Human-Only, the superior variant in split test 1, vs Human–AI Collaboration. All parameters were set symmetrically, including identical targeting, Automated Creative Optimization turned off, and a one-day duration per split, to reduce unwanted differences. The rationale for sequential A/B testing was to limit cross-arm interference that typically arises in simultaneous three-arm tests, including auction competition, mutually influencing budget pacing, non-independent algorithm learning phases, and audience overlap. As a consequence, day effects may still occur because the two splits took place on different days.

Stimuli

The stimuli consisted of three thirty-second videos with similar themes and styles to minimize confounders (van Berlo et al., 2024), so that the primary difference was the extent of AI involvement in the creative process:

- A. Human-Only (A): All creative stages were performed by humans. Non-generative tools could be used. This served as the benchmark and experimental control.
- B. AI-Only (B): All creative stages were performed by AI. Humans provided only prompts and minor corrections without adding new content.
- C. Human–AI Collaboration (C): AI produced an initial draft. Humans made substantive revisions and final decisions for narrative, visuals, and audio.

Labels A, B, and C are used consistently in the results to facilitate comparison across conditions.

Targeting and execution

Targeting included TikTok users in Indonesia aged 18 to 34 (Nurhayati Wolff, 2022). Each split test ran for one day with a total budget of IDR 600,000, that is IDR 300,000 per ad. The initial allocation of IDR 200,000 per ad was then adaptively increased to reach sufficient completed views, following CPM and CPV based adjustment recommendations.

Measurement and Outcome

- Primary outcome: *Completion rate (CR)*. The proportion of viewers who watched the ad to completion. CR is used as an indicator of deeper message processing consistent with ELM (Cacioppo et al., 1986; Feng et al., 2023). In short-form video contexts, CR reflects the success of sustaining attention to the end (Salminen et al., 2024).
- Secondary outcomes: (1) *6-second view rate* as an indicator of early engagement prior to further elaboration (Wang et al., 2020). (2) *Average watch time (AWT)* to contextualize viewing duration, reflecting a combination of central and peripheral processing routes (Feng et al., 2023).
- Exploratory metrics: CTR, likes, comments, and shares were recorded for transparency and engagement patterns, yet were not used for inferential testing due to low frequencies that create a floor effect (Salminen et al., 2024).

All data were extracted directly from TikTok Ads Manager at the ad group level. As an ethical consideration for an advertising experiment, reporting is limited to aggregate metrics from TikTok Ads Manager without access to personally identifiable data. Ad exposure followed platform policies and was categorized as minimal risk, equivalent to ordinary ad exposure.

Analysis

Comparisons used the two-proportion pooled z-test (Attwood et al., 2022) (two-sided, $\alpha = 0.05$). Differences in proportions are reported as Δ in percentage points, denoted pp, with 95% CIs calculated via the score or Newcombe approach, and the risk ratio (RR) is provided for relative effects. The B vs C comparison was not analyzed because the tests were not simultaneous.

Power and Sensitivity (a priori)

Because baselines were uncertain, two conservative scenarios were used: $p = 0.50$, which yields maximum variance, and $p = 0.30$, which is typical for short-form video. With $\alpha = 0.05$ and power = 0.80, detecting a Δ of approximately 1.0 pp requires about 39,000 views per ad for $p = 0.50$ and about 33,000 views per ad for $p = 0.30$. Given historical CPV and a budget of roughly IDR 300,000 per ad, the minimum detectable effect below 1 pp was projected to be achievable so that small but operationally meaningful differences could still be detected. These estimates support the interpretation of A vs B and A vs C while recognizing that the non-simultaneous design limits cross-arm generalization.

2.3 Phase 2: In-depth Interviews

Participants and procedure

After the quantitative experiment, the study proceeded with semi-structured interviews (± 30 –45 minutes) to probe the psychological mechanisms underlying audience responses to the three ad variants. Six participants aged 18 to 34 who were active TikTok users were purposively recruited, and each participant viewed only one stimulus variant to elicit natural responses. Online interviews were recorded with permission in audio and video, and were transcribed verbatim. This study complied with the research ethics guidelines at Universitas Pendidikan Indonesia. All participants provided written informed consent. Identities were pseudonymized with codes P001 to P006, and data were stored in encrypted media with restricted researcher access. Participant composition was as follows: Human-Only, P001 architecture student and P002 agency photographer videographer; AI-Only, P003 psychology student and P004 graphic designer; Human–AI Collaboration, P005 commercial director and P006 freelance photographer videographer.

Interview Protocol

The protocol followed Creswell and Creswell (2023) and the ELM framework. Sessions began with an introduction, purpose, and informed consent, followed by warm-up questions about TikTok use. Participants then viewed the assigned stimulus via visual elicitation and answered descriptive recall and structural recognition questions after a second viewing to surface additional detail. The core section examined central-route factors such as argument quality, relevance, and persuasiveness, as well as peripheral-route factors such as visuals, music, effects, and emotions, in addition to AI-related perceptions of authenticity and trust (Cacioppo et al., 1986). Questions also followed up on quantitative findings, for example, lower completion in AI-Only and higher engagement in Human–AI Collaboration, to enable mixed-methods integration.

Recording and transcription

Interviews were recorded with permission in audio and video, transcribed verbatim, and manually verified. All data were stored on encrypted media. Identities were pseudonymized as P001 to P006, and data access was restricted to the researcher.

Qualitative data analysis

Data were analyzed using Creswell's Thematic Analysis steps: (1) preparing and organizing data (transcript, memos); (2) reading and writing reflective notes; (3) systematic open coding; (4) constructing and reviewing themes; and (5) presenting findings with interpretation that links themes to ELM, AI perceptions, and authenticity. NVivo software was used to manage the analysis.

Trustworthiness

Qualitative validity was enhanced through brief member checking, triangulation with quantitative metrics, an audit trail and codebook, and researcher reflexivity.

2.4 Data Integration (Mixing at Interpretation)

Data were integrated using a mixing at the interpretation phase (Creswell & Creswell, 2023), which is central to the explanatory mixed-methods design. In this strategy, quantitative and qualitative findings are compared side by side to obtain complementary insights. For example, when quantitative data show differences in completion rates across ad groups,

interview data are analyzed to explain the psychological factors that underlie those differences. This approach enables more comprehensive meta-inferences about audience responses to the ads and aligns in-tending to follow up on quantitative results (Creswell & Creswell, 2023).

Ethical considerations and disclosure

Consistent with risk minimization principles for online advertising, quantitative reporting is limited to aggregate metrics from TikTok Ads Manager without personal identifiers. In contrast, qualitative interviews were conducted with written informed consent. Recordings were transcribed verbatim, identities were pseudonymized as P001 to P006, and data management limited access to the research team. In line with findings on AI look and trust, we applied proportional disclosure of AI’s role when its contribution was material to visuals or audio while preserving message fluency. The creative process followed a human-in-the-loop principle in which final decisions for narrative, visuals, and audio rested with humans to mitigate misrepresentation and deepfake risks and to ensure accountability. Intellectual property rights were respected by using original or licensed assets. This paragraph consolidates ethical practices applied in both the experiment and interviews so that cross-method interpretation proceeds transparently without repeating technical details presented earlier.

3. RESULTS AND DISCUSSION

3.1 Quantitative Results

3.1.1 Brief Description

The experiment comprised two separate split tests on TikTok Ads Manager: Split-1 compared Human-Only (A) with AI-Only (B). Split-2 compared Human-Only (A), the superior variant in Split-1, with Human–AI Collaboration (C). All campaign parameters were equalized, and Automated Creative Optimization was turned off. The primary outcome was Completion rate (CR, 100%), defined as the ratio of completed views to total views. Secondary outcomes were the 6-second view rate, defined as the ratio of views equal to or greater than 6 seconds to total views, and Average watch time (AWT, seconds). All rates used total views as the denominator.

3.1.2 Metric Summary by Ad

Table 1 Summarizes the key metrics with rounding applied as appropriate.

Ad performance by split test (denominator equals total views)

Stimuli	Total views	Completed	CR (%)	6s views	6s rate	AWT (s)	Rp/Completed	Rp/6s view
Split-1 A (Human)		370	0.82%	2,724	6.01%	3.28	798	108.4
Split-1 B (AI)	83,104	520	0.63%	3,831	4.61%	3.21	586	79.5
Split-2 A (Human)	44,618	928	2.08%	8,091	18.13%	5.29	307	35.2
Split-2 C (Human–AI)	68,909	2,643	3.84%	17,832	25.87%	6.57	119	17.7

Note: CR = completed/total views; 6s rate = views \geq 6s/total views. . All rates are shown with two decimal places for reporting consistency, and counts (n) are reported as observed in **Table 1**.

Descriptively, in Split-1, ad A (Human-Only) slightly outperformed B (AI-Only) on both CR and the 6-second view rate. In Split-2, ad C (Human–AI Collaboration) outperformed A (Human-Only) with a substantially larger margin. From an efficiency perspective, IDR per completed view and IDR per 6-second view for Human–AI were lower on an exploratory basis, which provides cost context per viewing outcome without affecting the main inference. Secondary engagement metrics showed CTR \approx 0% (very few clicks; A = 1, B = 0, C = 2) and small variation in likes, comments, and shares (for example, likes: A = 146; B = 183; C = 204). Because of a floor effect and because these metrics do not change the main conclusions, they were not tested inferentially. As a complement, AWT is reported descriptively to contextualize viewing duration and is not included in inferential testing.

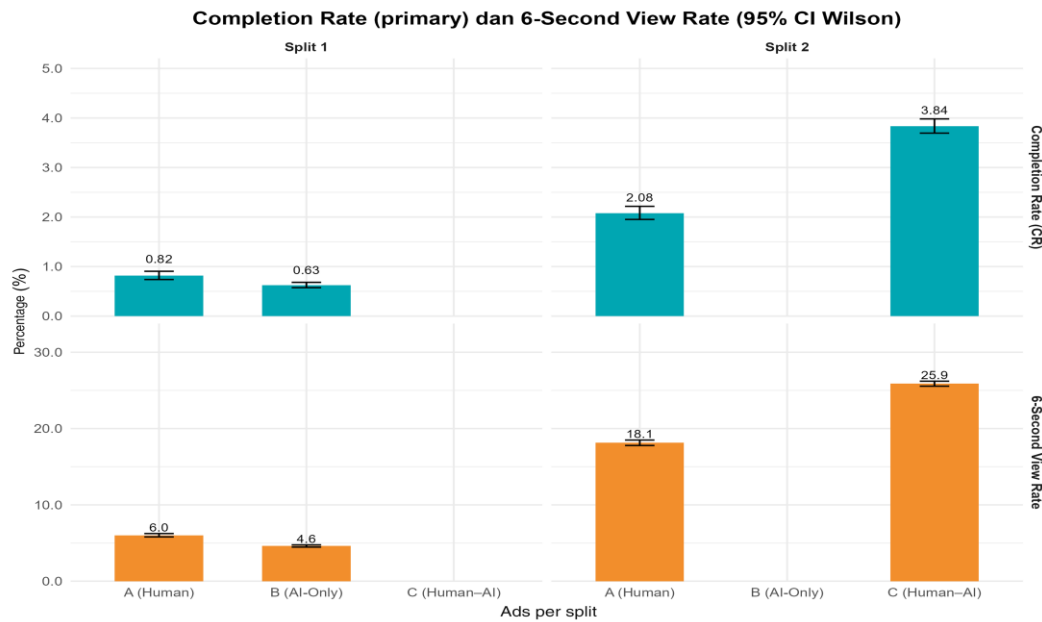


Figure 2. CR (primary) & 6-s View Rate (95% CI, Wilson) for Split-1 A vs B and Split-2 A vs C; denominator = total views; Pair-wise tests were non-simultaneous.

3.1.3 Inferential Comparisons (Two-Proportion z-test, two-sided, $\alpha=0,05$)

Confidence intervals for proportions used the score or Newcombe approach, and differences in proportions are reported as Δ in percentage points (pp). Decimal notation consistently uses a period. In addition to the p-value, Δ (risk difference, pp), the 95% CI, and the risk ratio (RR) are reported.

Table 2. Summary of pair-wise proportion tests for Split-1 (A vs B) and Split-2 (A vs C).

Δ is reported in pp with 95% CI (Newcombe); RR is reported with 95% CI. CR is the primary outcome.

Split	Comparisons	Outcome	Rate A (%)	Rate B/C (%)	Δ (pp) [95% CI]	RR [95% CI]	Z, p-value
1	A (Human) vs B (AI-Only)	CR (primary)	0.82	0.63	+0.192 [+0.093; +0.291]	1.31 [1.14; 1.49]	6.28; p<0.001
		6-s View Rate	6.01	4.61	+1.409 [+1.147; +1.670]	1.31 [1.25; 1.37]	10.95; p<0.001
2	A (Human) vs C (Human-AI)	CR (primary)	2.08	3.84	-1.756 [-1.951; -1.560]	0.54 [0.50; 0.58]	-21.38; p<0.001
		6-s View Rate	18.13	25.9	-7.744 [-8.228; -7.259]	0.70 [0.68; 0.72]	-30.36; p<0.001

As shown in **Figure 2** and **Table 2**, CR (primary) and 6-second view rate share a consistent pattern: Split-1 A > B and Split-2 C > A. Proportion tests confirm that for CR: $\Delta = +0.192$ pp (A vs B) and $-1,756$ pp (A vs C Both are statistically significant, with RRs of 1.31 and 0.54, These results are directionally aligned with the 6-second view rate. Given the non-simultaneous pair-wise design with two comparisons, causal conclusions are bounded. AI-Only tends to perform weaker than Human-Only, whereas Human-AI Collaboration performs strongest in this context.

3.1.4 Power and Sensitivity (Brief a priori)

Given baseline uncertainty, power planning used a conservative scenario with $p = 0.50$ (maximum variance) to maximize the binomial variance $p(1 - p)$ (Fleiss et al., 2003), with $\alpha = 0.05$ and power = 0.80 following common planning conventions (Biau et al., 2010; Cohen, 1988). Under these parameters, a minimum detectable effect (MDE) \approx of 1.0 pp requires about 39.000 views per ad. Based on historical CPV \approx IDR 3.7–6.5/view, an allocation of IDR 200,000/video is projected to yield \approx 30.8–54.1 thousand views (MDE \approx 1.13–0.85 pp, $p = 0.50$), whereas IDR 300,000/video is projected to yield \approx 46.2–81.1 thousand views (MDE \approx 0.92–0.70 pp, $p = 0.50$). The implication is that IDR 300,000/video reduces the MDE to < 1 pp, so the study is sufficiently sensitive to detect small yet operationally meaningful differences. These estimates support the interpretation of A vs B and A vs C while recognizing that the non-simultaneous design limits cross-arm generalization.

3.2 Qualitative Findings

The qualitative analysis identified five themes: (1) AI perception and authenticity, (2) central-route processing (ELM), (3) peripheral-route processing, (4) viewing behavior, and (5) comparative preference. These themes describe patterns shared across participants and clarify how judgments differed across the three creative conditions: Human-only, AI-only, and Human–AI collaboration.

3.2.1 AI Perception and Authenticity

Audiences judged authenticity through the visible “production traces,” especially facial expressions, emotional tone, and the balance among visuals, audio, and narration. In Human-Only content, the sense of “realness was easier to detect because affective cues were legible: *“if it is made by humans...there will be expressions”* (P001, Human-Only), which aligns with P002, *“When it is produced directly, you can feel the emotion, AI-made work will not feel the same”* (P002, Human-Only). As a result, human-delivered content tended to be seen as credible and emotionally relatable.

Participants also differentiated AI’s role in production. AI was accepted when used as an assistive tool to add effects or elements without replacing the human source: *“it depends on the production mechanism too, if AI is only a supporting platform to create elements or effects ... it is still made by humans”* (P002, Human-Only). In AI-Only content, the AI feel was quickly detected and often reduced trust and viewing intention: *“the visuals are cool, but I immediately noticed it was AI generated”* (P003, AI-Only); *“the AI is obvious...the feel is lacking...so I did not feel like watching it...it reduced my trust”* (P004, AI-Only). Even the aesthetic strengths could appear “too perfect,” signaling artifice: *“they make it great, but because it is too perfect, it looks like AI... that becomes a loophole in production”* (P005, Human–AI Collaboration). In this context, the distinctive visual or audio signatures of generative content are referred to as the AI look, for example, uniform textures or lighting and motion, or voice-over rhythms that feel synthetic. Without human elements, these traces can create a faux-real impression that suppresses perceived authenticity.

Human–AI Collaboration occupied a productive ambiguity when the proportions were balanced. Respondents valued AI footage or effects blended with real footage and anchored promptly by human elements: *“In my view, it is very creative to combine AI with real footage because I always like that”* (P005, Human–AI). P006 recognized this “blend,” *“it looks real ... I can accept AI content ... it is creative in utilizing technology,”* while noting a tradeoff: *“it is creative yet less natural”* (P006, Human–AI). AI is most noticeable in the transitions: *“the transition clearly looks like AI”* (P003, AI-Only). Therefore, if AI effects appear in the opening, human elements should enter quickly. This timing turns ambiguity into added value rather than a faux-real distance. Overall, authenticity is not a simple human vs AI binary: It depends on role allocation during production. Human-Only tends to excel in warmth and credibility through expression and emotion. AI-Only can be visually strong, yet without quick human context, its AI nuances may reduce trust and trigger skipping. Human–AI Collaboration is the most acceptable when AI provides an aesthetic spark that is immediately bridged by a human presence that anchors meaning.

3.2.2 Central Route

The Central Route engages when viewers quickly grasp a core message, can follow the reasons that support it, and receive practical details about what is offered, for whom, how to access it, and when or where it occurs. An early visual cue should be followed right away by a clear explanation so curiosity moves from simple attention to real understanding. Some participants described a strength as resistance to skipping. As P001 put it, *“a good ad is an ad that is hard to skip”* (P001, Human-Only). Directed curiosity works when the opening gives a small hint and then explains it immediately with words or visuals. P002 illustrated this pattern: *“at the beginning ... training... people do not know, so they might watch longer ... Oh what is happening here?”* (P002, Human-Only). In practice, a brief teaser should be followed promptly by a cause-and-effect story that leads the viewer to the core message.

By contrast, when initial context or message reinforcement is missing, cognitive processing stalls. In AI-Only, participants judged the arguments weaker and less focused: *“not convincing ... the core message is not very strong”* (P003, AI-Only); and *“from the start I did not get a clear context”* (P003, AI-Only). Without early clarity on the what and the why, attention does not progress to elaboration, and viewers are more likely to skip. Participants also emphasized the value of a storyline that connects a problem, a solution, and a call to action. Such structure helps viewers assess benefits and imagine their place in the scenario: *“In my opinion, if an ad is effective ... it is more about the story, there is storytelling behind it”* (P004, AI-Only). With a coherent narrative, reasons to keep watching become clear, and the call to action feels warranted.

Extending this logic, results were strongest in Human–AI Collaboration when a human voice or presence entered soon after the visual hook. In this arrangement, AI refines the look and rhythm, while the human element clarifies the core message and provides signposts toward action. Participants reflected this view: *“message-wise it is already clear”* (P005, Human–AI) and *“the information was very clear ... the invitation, location... were very clear”* (P006, Human–AI). The human presence adds emotional nuance and organizes information so that audiences can process arguments and reach a decision. Taken together, Central Route activation depends on three connected elements. First, begin with a hook and explain its context quickly so curiosity becomes comprehension. Second, present clear arguments alongside complete logistical

information so that understanding can form and deepen. Third, pair strong visuals with human guidance to accelerate the shift from attention to elaboration, which in turn makes the advertisement “hard to skip.”

3.2.3 Peripheral Route

The Peripheral Route operates when a strong first impression captures attention through visuals, background music, or the narrator’s voice, often within seconds. Because of that speed, the hook, the fit between tone and emotion, and the coherence of images and audio shape retention. Participants put it simply. An ad is appealing when “*it can make me curious*” (P001, Human-Only), and the first impression should ignite emotions that matter to the audience, “*it makes us excited and fired up*” (P001, Human-Only). In this context, the voice-over functions as an attention anchor: “*the voice-over makes my heart race and fits well*” (P001, Human-Only).

In Human-Only content, the initial appeal rests on natural expression and tight alignment among elements. Dramatic visuals that match a well-chosen voice-over build tension from the first second: “*the visuals are very good, dramatic, and intense. The voice-over fits perfectly. The cinematic storytelling is already strong*” (P002, Human-Only). This coherence turns mere exposure into valuable attention because early cues reinforce each other.

By contrast, AI-Only content offers high visual spectacle with “*vibrant colors ... distinctive transitions ... attractive effects*,” yet it is often not supported by equivalent emotional scaffolding: “*the audio is not very prominent ... it does not match the visuals*” (P003, AI-Only). As a result, the initial sense of “*that is cool*” fades quickly because the focus tends to be visual show-off rather than a hook that builds curiosity (P003, AI-Only). Even when cinematography and color are praised, participants still detect technological traces that thin out naturalness, “*you can still see AI’s imperfections*” (P003, AI-Only), which means the Peripheral Route in AI-Only often stops at admiration without progressing to engagement.

In Human–AI Collaboration, the Peripheral Route is more stable because technical polish is paired with measured emotional orchestration. Audio is perceived as aligned with persuasive goals, “*it sounds hopeful, not angry*” (P005, Human–AI), while the visuals are considered cinematic: “*the treatment is cinematic ... the writing is good, the background score is good ... the lighting, cinematography, and color grading are excellent*” (P006, Human–AI). When these elements are arranged to reinforce one another, the emotions needed to sustain attention emerge without sacrificing viewing comfort. Taken together, three lessons characterize the Peripheral Route. First, pair a curiosity-sparking hook with an appropriate emotional tone so attention does not fade quickly. Second, ensure coherence among images, rhythm, and voice-over because strong visuals are not enough without audio that adds emphasis and emotional direction. Third, Human–AI Collaboration offers an effective space to combine aesthetic strengths with emotional control, while AI only risks stopping at admiration if its audio orchestration is weak. With this foundation, the Peripheral Route opens the door to attention and prepares viewers to enter the Central Route at the next explanatory moment.

3.2.4 Viewing Behavior

On short-form video platforms, decisions to continue, skip, or complete occur within seconds. These decisions reflect the interplay of curiosity, contextual clarity, and audiovisual coherence. When this sequence holds together, viewing time increases. When any part is missing, skipping becomes more likely. In Human-Only content, a carefully arranged opening sustains attention until key information appears. An opening that shows “training” without immediately naming the event keeps viewers watching as they search for answers: “*at the beginning, training it was not immediately revealed what the event would be, so people might watch longer, ‘Oh what is going on’*” (P002, Human-Only). The mechanism is simple. Start with a hook, then follow with narrative clarification so brief exposure becomes sustained interest.

In AI-Only content, viewing decisions depend strongly on contextual clarity and the precision of the hook. When both are weak, skipping happens quickly: “*there must be clear context and a hook... otherwise they will skip quickly*” (P003, AI-Only). Curiosity still matters across creators: “*whoever the content creator ... is, if they make us curious, it is effective*” (P004, AI-Only). Visual appeal by itself is not enough without context and a guiding hook. Platform norms also shape behavior. Viewers arrive for fun and entertainment, so ad content that begins in an entertaining register tends to be more forgivable even when it is later revealed to be an ad: “*TikTok’s initial purpose is for fun and humor then you suddenly realize ‘Oh this is an ad’ that is what makes you watch it to the end*” (P004, AI-Only). In other words, an entertainment wrapper that fits platform expectations can encourage completion.

In Human–AI Collaboration, the most stable pattern appears when a visual hook is followed promptly by a human narrative. In this ecosystem, the opening is decisive: “*on TikTok everything starts from the opening hook*” (P005, Human–AI). After that, coherence among visuals, music, and voice-over consolidates interest: “*although the AI is not perfect, the visuals are good ... the music is good ... the narration is also good*” (P006, Human–AI). The AI traces remain noticeable, yet clean aesthetics combined with clear explanation are often enough to keep viewers to the end. Overall, viewing behavior is guided by three decision chains. First, the opening second hook ignites curiosity. Second, quick and relevant context prevents attention from stopping at brief admiration. Third, audiovisual coherence plus need-oriented explanation encourages completion. Human-Only tends to excel when human expression channels curiosity toward meaning. AI-Only requires disciplined context and hooks so that visual prowess is not wasted. Human–AI Collaboration is most consistent when strong

visuals are anchored by a human voice-over, allowing the sequence from curiosity to understanding to completion to unfold smoothly.

3.2.5 Comparative Preference

Respondents’ preferences across the three ad variants follow a consistent pattern. Emotional closeness and a sense of realness are primary criteria. Technical polish is appreciated as long as it does not erase human traces. In Human-Only content, the most prominent strengths are expressions and gestures that participants consider difficult for AI to replicate. P001 put it. The expression of people exercising feels present in human-made ads, whereas AI-generated versions tend to be flat or uniform. This advantage strengthens authenticity, although the final standing still depends on the creative concept and the quality of the narrative, with judgments ranging from “it is just okay” and “without AI it is already possible” (P001, Human-Only) to “it is interesting” (P002, Human-Only). In AI-Only content, the first impression is often captivating. Yet, the final preference tends to be neutral to cool compared with other ads: “to be honest, I find this ad just ordinary...easy to forget” (P003, AI-Only); “just okay” (P004, AI-Only). Acceptance is possible but conditional. Clear context and a relevant hook are needed from the outset. As one participant said, “if it is made fully by AI, that is fine, but there must be a clear context” (P003, AI-Only). Without these anchors, visual polish reads as a display with limited meaning.

In Human–AI Collaboration, preferences tilt more positively. Collaboration is viewed as creative because it leverages technology without losing the human aspect. “It is very creative to combine AI with real footage” (P005, Human–AI). Participants also noted value and exclusivity. Large clients tend to favor what feels real and authentic, so the blend is considered better than other options, “it turns out cool” (P005, Human–AI), and “wiser than full AI” (P006, Human–AI). Practical considerations reinforce this view. AI can overcome production constraints when resources are limited, yet “if there is a choice not to use AI, it is preferable not to use it” (P006, Human–AI). Overall, Human–AI receives the highest preference because it combines efficiency and technical aesthetics with credibility and human warmth. Human-Only remains strong when expression and narrative are well executed. AI can only attract attention at first sight, but without early context and a guiding hook, viewers do not carry that attention through to lasting preference.

3.2.6 Cross-Theme Synthesis

This cross-theme synthesis reinforces ELM patterns in short-form video contexts. Peripheral cues in the opening seconds, including the hook, visual rhythm, and the quality of audio or voice-over, act as the main entry points to attention. Human–AI Collaboration tends to perform well at this stage because AI’s visual appeal is tied immediately to a human voice or presence. Endurance of viewing and acceptance of the message are then shaped by central cues, namely clarity of the core message, perceived credibility, and a natural delivery. Human cues, such as recognizable faces or a steady voice-over, strengthen clarity and credibility along the central route while preserving entertainment value along the peripheral route. In contrast, an intense AI look without human elements heightens a faux real impression and lowers perceived authenticity, which weakens early evaluations such as trust and liking and reduces the motivation to keep watching. Practically, the most stable pattern is to deploy AI as a brief visual spark and then introduce human elements without delay. This sequence links early attention to structured explanation, supports elaboration, and increases the likelihood of viewing completion.

3.3 Discussion and Integration of Findings

To aid readers, **Table 3** maps qualitative codes M1 to M5 to theme names, brief definitions, and their links to quantitative metrics.

Table 3. Mapping of Qualitative Themes and Links to Metrics (Brief codebook)

Code	Theme Name	Operational Definition	Link to metrics
M1	AI perception and authenticity	The degree to which visuals and audio feel real rather than synthetic, and the credibility of the perceived source	6s-rate↓, CR↓ when the AI look is strong without a human anchor or element.
M2	Peripheral route ELM	Opening cues in the first 0-2 seconds that capture attention and trigger emotion	6s-rate↑ (entry into viewing)
M3	Central route ELM	Processing of core message and arguments through to the end, including perceived credibility	CR↑ (watched to completion)
M4	Creative preference	Comparative preference for Human-Only, AI-Only, or Human–AI and the stated reasons	Supports the ordering C > A > B
M5	Viewing behavior	Patterns of skip, continue, and replay, and the levers that extend viewing duration	6s-rate captures initial entry into viewing.; CR captures the final outcome

3.3.1 Cross-Method Synthesis (Quant ↔ Qual)

Quantitative results show two consistent patterns across separate comparisons: (1) on the same day, Human-Only (A) outperformed AI-Only (B) on Completion rate and 6-second view rate; (2) on a different test day, Human–AI Collaboration (C) clearly surpassed Human-Only (A). The qualitative trajectory provides the mechanism that links these outcomes. Perceptions of AI and authenticity (M1) shape the opening moments, while peripheral and central routes (M2 and M3)

explain how attention is first captured and then carried through to message understanding. Creative preference (M4) and viewing behavior (M5) describe how these processes translate into choices to continue or to complete. Across these themes, audiences value an early human presence as a credibility cue. Human–AI collaboration adds variation in rhythm, message structure, and scene strength, which together support processing through to completion. Taking the non-simultaneous design into account, the integrated synthesis indicates a functional ordering of $C > A > B$ in similar contexts. This ordering is indicative and should not be interpreted as a causal estimate.

3.3.1 A Links to Prior Findings

Prior evidence clusters into three areas. (i) short-form video ads and the importance of the first-second hook. Analyses of TikTok ads show a sharp engagement drop within the first quarter of the runtime, making the opening seconds crucial for preventing early churn, consistent with Salminen et al. (2024). (ii) human cues such as faces and voice-overs for trust and attention. The AI trust literature highlights embodiment and proximity cues as credibility anchors that reduce initial uncertainty and move viewers from shallow attention to deeper processing (Cacioppo et al., 1986; Feng et al., 2023). (iii) effects of AI disclosure on perceived authenticity and trust. Exposure to AI content often produces ambivalence. The machine heuristic of objectivity and efficiency may be valued, yet eeriness and the AI look can reduce perceived realness. Proportional disclosure helps reduce anxiety and sustain trust (Baek et al., 2024). Integrating these strands, this study shows that Human–AI collaboration, rather than full replacement, optimizes the balance between authenticity reinforced by human cues and production efficiency and structural orchestration supported by AI in TikTok contexts (Yao et al., 2024).

3.3.2 Mechanisms in the ELM Framework

Within the Elaboration Likelihood Model, the 6-second view rate indicates activation of peripheral cues that capture early attention (M2), while completion rate reflects central elaboration that carries processing to the end (M3) (Cacioppo et al., 1986). When a creative stimulus delivers an effective early hook, the chance of deeper processing rises. As P005 noted, “on TikTok everything starts from the opening hook” (P005, Director, 06/10/2025). Aligned with the quantitative results, $A > B$ on CR at $\Delta = +0.192$ pp with $p < .001$ indicating an advantage associated with a human presence, while $C > A$ at $\Delta = -1.756$ pp for A minus C with $p < .001$ suggesting that AI-supported structure, rhythm, and content fit can reinforce central processing and raise completion. These patterns mirror prior ELM findings. Effective peripheral cues increase the likelihood of central processing when argument relevance and quality are adequate (Cacioppo et al., 1986; Feng et al., 2023). In short, a human presence supplies authenticity and clarity that counter the AI look, reducing faux real impressions and sustaining the persuasion flow from attention to elaboration.

3.3.3 Authenticity, the “AI Look,” and AI Role Disclosure

Theme M1 places perceived authenticity as a prerequisite for engagement. The AI looks, for example, for lighting or textures that appear “too perfect,” which can undermine perceived realness. P005 note that the lighting and textures felt “too good,” illustrating the risk of synthetic visuals (Puspasari et al., 2025). This helps explain B’s weakness. Without a human anchor, highly synthetic cues lower early credibility. Public responses in the experiment echo this pattern. A viewer asked, “Was this made by AI?” and another replied, “Do you even need to ask?” which signals that audiences can detect the AI look and that this perception can harm event evaluations. By contrast, C allows for augmentation while real human elements preserve authenticity. This aligns with prior work showing that rejection of the AI look can coexist with the benefits of proportional disclosure. Eeriness suppresses acceptance, while measured transparency maintains trust (Baek et al., 2024).

3.3.4 Why Human-AI Collaboration Prevails (M4-M3)

In Creative Preference insights (M4), collaboration casts AI as an augmentation layer that supports variation in cuts, pacing, transitions, and overall flow. Humans preserve warmth, intonation, and narrative logic, which are the elements most closely tied to Central Route elaboration (M3). Informants repeatedly emphasized voice-over intonation as the audio path that guides attention into elaboration. Functionally, AI serves as a temporal and structural augmentser that raises efficiency and scalability, while credibility and emotion remain grounded in human presence. This division of roles aligns with recent reviews and surveys in AIGC and advertising, which report strong performance when AI enhances structure and humans carry meaning and trust (Madathil, 2025; Yao et al., 2024).

3.3.5 Moderators and Boundary Conditions (M5, Category, Disclosure)

Qualitative integration indicates several moderators that bound the interpretation of the findings. First, category or brand tier. For categories that require real representation or signal prestige, audiences tend to prioritize realness and human presence, as authenticity cues function as credibility anchors (Salminen et al., 2024). This tendency is reflected in the present study, where participants consistently emphasized facial expressions, emotional tone, and vocal intonation as indicators of credibility, particularly in Human-Only and Human–AI Collaboration content. Second, audience segmentation characteristics represent an important boundary condition that helps explain differences in audience perspectives. Although

this study did not aim to statistically compare demographic groups, the qualitative sample offers interpretive insight into how audience background shapes perception. Participants were aged 18–34 and active TikTok users, with diverse educational and professional backgrounds spanning architecture, psychology, photography, graphic design, and commercial directing. This profile reflects a digitally literate audience segment with relatively high awareness of AI-generated content and familiarity with contemporary creative production practices. Within this segment, participants were able to quickly detect AI-generated cues (the “AI look”) and to articulate nuanced distinctions between AI as a supportive creative tool and AI as a full content generator. This sensitivity helps explain why AI-Only content was more readily perceived as synthetic and less trustworthy, whereas Human–AI Collaboration was evaluated more positively. These perspectives may differ among audiences with lower AI awareness, different age cohorts, or less exposure to digital creative workflows, where AI-generated aesthetics may be perceived as novel rather than as a credibility risk. Third, the disclosure strategy acts as a further moderator. Clear yet proportional disclosure of AI’s role helps reduce AI anxiety and maintain trust without disrupting narrative flow. Consistent with interview findings, overt or dominant AI presence without contextual anchoring tended to heighten skepticism, whereas AI embedded within a human-led narrative was perceived as more acceptable and credible.

Fourth, production tactics moderate audience responses through the management of the AI look. Elements such as lighting, textures, transitions, and voice-over should be adapted so that they blend with real footage and human audio cues. Participants indicated that overly “perfect” visuals or synthetic vocal rhythms amplified perceptions of artificiality and weakened emotional engagement. Practical adjustments, such as calibrated color grading, the inclusion of natural room tone, and refined voice-over prosody, help mitigate these effects while preserving AI’s aesthetic advantages. Fifth, viewing control points shape transitions from attention to elaboration in short-form video advertising (M5). The opening zero to two seconds provides the primary hook through peripheral cues, the two to six second window establishes rhythm and contextual clarity, and the later segment emphasizes message delivery and call to action. The findings suggest that Human–AI collaboration performs most consistently when AI-driven visual stimulation is introduced early but is quickly anchored by a human voice or presence, enabling a smooth shift from peripheral attention to central route processing.

Rules of Human-AI collaboration

Synthesizing these moderators, the findings point to several guiding principles regarding the extent and form of Human–AI collaboration across creative domains. First, role allocation emerges as a key principle. AI is most effective when applied to visually intensive and structural elements, such as scene composition, transitions, and pacing, while humans should retain control over meaning-making elements such as narration, emotional expression, and message framing. Second, temporal anchoring is critical. Human presence should be introduced early in the viewing sequence, ideally within the first six seconds, to stabilize credibility and prevent premature skepticism triggered by the AI look. Third, authenticity preservation functions as a limiting rule. AI should not become the primary source of emotional or moral cues, as this role is more effectively fulfilled by human presence. Fourth, proportional disclosure operates as a regulatory principle, whereby transparency about AI use should be sufficient to reduce AI anxiety without interrupting narrative immersion. Finally, context sensitivity constrains the degree of collaboration. In high-risk or prestige-oriented domains, Human–AI collaboration with a dominant human anchor is more appropriate, whereas in utilitarian, informational, or budget-constrained contexts, higher degrees of AI involvement may be acceptable, provided that minimal human cues remain present.

Practical implications

Based on these moderators and collaboration rules, several recommendations emerge. (i) For prestige categories or brands with high reputational risk, Human–AI Collaboration with a clear human presence (e.g., face or voice-over) should be prioritized. (ii) For utilitarian categories or constrained budgets, Human–AI or even AI-Only content may remain viable, provided that key human elements such as narration or vocal cues are retained. (iii) In the critical 0–2 second phase, AI visuals may function as an attention spark, but a human presence should be introduced quickly to anchor credibility. (iv) Proportional disclosure of AI use is recommended to reduce AI anxiety without breaking narrative flow. Together, these guidelines reduce risks associated with the AI look and preserve the pathway from peripheral cues to central elaboration.

3.3.6 Integration Implications (Joint Inference and Joint Display)

Integration follows three mixed-methods principles: (1) Convergence, which is directional alignment of findings. (2) Complementarity, which offers mechanisms that explain the effects. (3) Expansion, which extends coverage. Quantitatively, A vs B shows Human-Only > AI-Only, whereas A vs C shows Human–AI > Human-Only. Qualitatively, human cues such as authenticity, warmth, and credibility trigger early attention, while AI augmentation, such as visual variation, rhythm, and emphasis, strengthens message structure through to completion. Taken together, the quantitative pattern of A > B and C > A, combined with the qualitative mechanisms, indicates a functional ordering of C > A > B for similar contexts. This ordering is indicative rather than causal because B versus C was not tested on the same day. Expansion is evident in the

precision and effect sizes from the quantitative side and in the timing and processes from the qualitative side.

Table 4. Joint display integrating quantitative and qualitative findings within ELM

Comparison	Main Outcome (Quant)	Precision & Significance	Related Qualitative Themes	Mechanism (ELM)	Representative Quotes	Integrative Inference
A (Human-Only) vs B (AI-Only)	CR: 0,82% vs 0,63% → Δ = +0,19 pp, RR≈1,31	95% CI Δ [+0,093; +0,291]; z = 6,28; p < 0,001	M1 AI Perception and Authenticity; M2 Peripheral Route	Human presence as a peripheral credibility cue increases early engagement and trust in the ad	“If it is made by humans, there will be expressions” (P001, Human-Only) “The visuals are cool, but I immediately noticed it was AI-generated” (P003, AI-Only);	A > B: Human presence secures early attention. AI-Only misses warmth and credibility to drive elaboration
A (Human-Only) vs C (Human-AI)	CR: 2,08% vs 3,84% → Δ = 1,76 pp, RR≈0,54	95% CI Δ [-1,951; -1,560]; z = -21,38; p < 0,001	M3 Central Elaboration; M4 Creative Preference; M5 Viewing Behavior	AI as an augments enriches structure and rhythm, which supports deeper central processing	“It is very creative to combine AI with real footage” (P005, Human-AI)	C > A. Collaboration adds rhythmic and structural variation while humans maintain clarity and intonation, so completion increases

3.3.7 Limitations and Future Directions

This study compared A vs B and A vs C on different days, so day effects could not be removed. For that reason, we treat the results as two separate comparisons rather than a single three-arm causal ranking, and there is no direct B vs C test. We used a sequential design to limit cross-arm interference that can happen in one auction pool, such as auction competition, mutual effects on budget pacing, non-independent algorithm learning, and audience overlap. The trade-off is that day effects may still influence the outcomes. For future work, a stronger design would run a simultaneous three-arm test using geo splits or a multi-cell setup so that each arm enters a separate auction. If that is not feasible, daily randomized block designs over at least three days with fixed day effects and counterbalanced orders, for example, B then A on some days and C then A on others, can reduce both day effects and interference. It will also help to expand the qualitative sample across categories and audience segments to test robustness. Finally, cost per completed view can be tracked as an exploratory indicator of efficiency, while completion rate and related outcomes remain the primary basis for inference.

4. CONCLUSION

This mixed-methods study demonstrates that the effectiveness of short-form video advertising on TikTok is strongly shaped by the configuration of human and AI involvement in the creative process. Across two sequential split tests, the quantitative results reveal a clear pattern. Human Only advertising significantly outperformed AI Only advertising on both Completion Rate and six-second view rate, while Human-AI Collaboration achieved the highest engagement levels, surpassing Human Only on the same metrics. These findings indicate that content generated solely by AI is less effective in sustaining attention, whereas collaborative use of AI can enhance performance when guided by human creative control. The qualitative findings clarify the mechanisms underlying these differences. Human elements, such as facial expressions, vocal intonation, and narrative delivery, function as credibility and authenticity cues that facilitate both peripheral and central route processing. In contrast, AI-Only content was frequently perceived as synthetic due to a recognizable AI look, which weakened trust and reduced viewers’ motivation to continue watching. Human-AI Collaboration mitigated this effect by allowing AI to support visual structure, pacing, and transitions, while humans retained control over meaning making, emotional expression, and message clarity. This configuration enabled peripheral cues supported by AI to capture attention and human cues to sustain central elaboration, resulting in higher completion rates.

Taken together, the integrated findings provide empirical support for the Elaboration Likelihood Model in short-form video contexts. Early engagement, reflected in the six-second view rate, is driven primarily by peripheral cues, while viewing completion depends on the successful transition to central route processing. Human-AI Collaboration facilitates this transition more effectively than either Human Only or AI Only production by combining aesthetic efficiency with perceived authenticity and trust. The principal implication of this study is that generative AI is most effective in short-form video advertising when used as an augmentative tool rather than a full creative replacement. For practitioners, strategies that integrate AI optimization with clear human presence offer a more effective and socially acceptable approach than content produced solely by AI. For research, these findings extend the literature on generative AI in advertising by providing experimental evidence from TikTok, a platform where engagement dynamics differ from video environments with longer durations. Future studies should employ simultaneous multi-arm designs, broader audience segments, and economic outcome measures to further validate and generalize these conclusions.

Data Availability Note

Aggregated metric summaries and anonymized transcript excerpts are available upon request for academic review.

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