



TIKTOK ENGAGEMENT CONSISTENCY AS DIGITAL RESILIENCE: STORYTELLING AND CONTENT QUALITY IN A LOCAL FASHION BRAND

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Abstract

Short-form video marketing is often evaluated through viral or high-performing posts, while less attention is given to whether engagement remains stable across a brand's content stream. This study examines the relationships of brand storytelling and content quality with engagement consistency on TikTok and assesses whether engagement consistency can serve as a content-level indicator of digital resilience. A quantitative, non-reactive, secondary-data design was applied to 40 publicly available videos posted by Eshnawn Studios from 22 June 2023 to 21 April 2026. Engagement Rate was calculated from views, likes, comments, shares, and saves, while storytelling and content quality were coded using a structured rubric and aggregated into six observation periods. Engagement consistency was represented inversely by the Coefficient of Variation of Engagement Rate and analyzed using descriptive statistics, Spearman correlation, exploratory regression, and sensitivity checks. Storytelling was strongly associated with higher engagement variability, while content quality showed a similar but statistically non-significant tendency. The Coefficient of Variation also distinguished stable from volatile periods, supporting engagement consistency as an exploratory indicator of content-level digital resilience. For fashion businesses, social media managers, and digital marketers, the findings support content planning that balances creative storytelling with repeatable formats, consistent product framing, and performance monitoring.

Keywords: engagement consistency; digital resilience; brand storytelling; content quality; tiktok marketing; local fashion brand



By Authors

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1. Introduction

Short-form video has become a central format in contemporary digital marketing because mobile-first platforms enable brief audiovisual messages to circulate rapidly beyond established follower networks. In Indonesia, TikTok's advertising resources indicated approximately 180 million users aged 18 years and above in late 2025, with potential advertising reach equivalent to 88.9 percent of the adult population, highlighting the strategic relevance of the platform for brand communication (Kemp, 2025). Social media also provides Micro, Small, and Medium Enterprises (MSMEs) with scalable opportunities for market visibility, customer interaction, and business continuity under relatively constrained resources (Patma et al., 2021). For local fashion brands, however, digital marketing performance involves more than producing isolated high-performing posts because sustained visibility also depends on whether audience responses can remain sufficiently stable across repeated content publications.

Online brand engagement provides a relevant response domain because brand engagement includes cognitive, emotional, and behavioral investment associated with brand interactions, while public platform reactions provide observable behavioral traces of audience response (Hollebeek et al., 2014). Recent short-form video research has mainly examined factors that explain engagement at the level of individual advertisements or posts. Performance expectancy, entertainment, tie strength, and sales approach have been associated with consumer engagement in TikTok advertising, while audiovisual characteristics such as colloquial expression, cadence, colorfulness, and visual prominence have also been linked with engagement behavior (Xiao et al., 2023; Zhang et al., 2025). Audience retention can also deteriorate rapidly during short-video advertising exposure, reinforcing the importance of content characteristics for attracting and maintaining attention (Salminen et al., 2024). Evidence from Indonesian fashion MSMEs similarly indicates that TikTok content quality is relevant to customer engagement, although the dominant analytical emphasis remains engagement intensity or immediate response rather than temporal stability across a continuing content stream (Yudhyani & Sukirman, 2025).

2. Literature Review

Brand storytelling and content quality represent two content attributes that can shape digital audience response through different but complementary mechanisms. Storytelling can connect product presentation with situations, emotions, identity, lifestyle, and symbolic meaning, while digital storytelling research also shows that coordinated brand-authored narratives can translate cultural or symbolic references into communicated brand meaning (Ben Aicha & Bouzaabia, 2023; Prasetia & Benyamin, 2026). Content quality can operate through visual clarity, informational usefulness, entertainment value, editing, message coherence, and media richness, which function as marketing stimuli capable of influencing audience cognition, affect, and behavioral response within the Stimulus-Organism-Response (S-O-R) perspective (Tian et al., 2022;

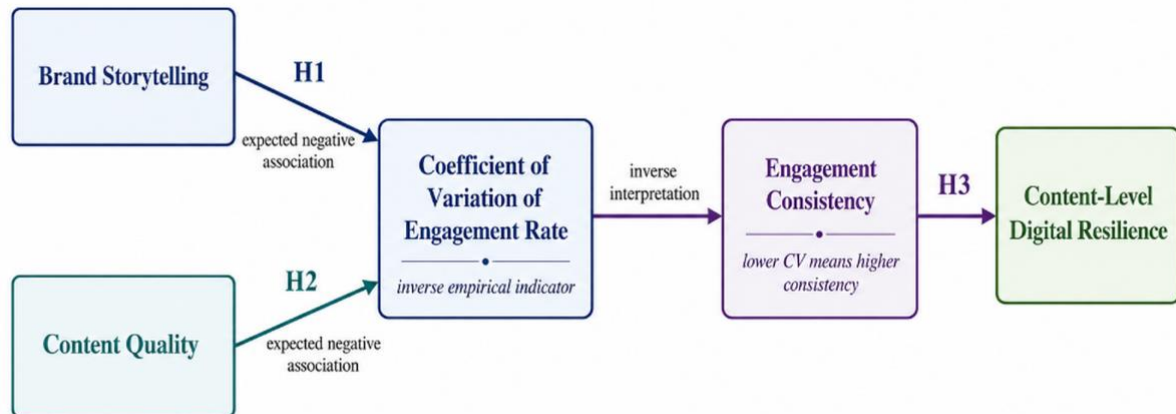
Yu et al., 2024). Existing evidence therefore provides a strong basis for expecting richer storytelling and higher content quality to improve audience responses, but positive audience response at the level of individual content does not establish whether comparable responses can be reproduced consistently over time.

Engagement magnitude and engagement consistency represent conceptually different dimensions of digital performance because a high average response can coexist with substantial variation across successive posts. Consistent social media communication has been associated with stronger brand-related outcomes among smaller enterprises, suggesting that regularity and continuity carry strategic value beyond isolated communication success (Aristana et al., 2024). Digital resilience literature similarly emphasizes the capacity of smaller firms to maintain performance, adapt to changing digital conditions, develop marketing capabilities, and apply coordinated, data-informed management practices (Hokmabadi et al., 2024; Prasetya, 2026)). However, resilience research has primarily addressed organizational capabilities, while short-form video research has predominantly explained engagement at the individual-content level, leaving limited understanding of how repeated engagement stability can be operationalized as a narrowly defined content-level signal of digital resilience.

The proposed framework extends the S-O-R logic from immediate audience response toward the regularity of observable responses across a brand's content stream. Stronger brand storytelling is expected to reduce the Coefficient of Variation (CV) of the Engagement Rate (ER) because coherent narrative cues may provide recognizable meaning and emotional continuity across repeated content, while higher content quality is expected to reduce the same variability by supporting clearer and more predictable audience processing ((Ben Aicha & Bouzaabia, 2023; Tian et al., 2022; Yu et al., 2024). H1 states that higher brand storytelling is negatively associated with the CV of ER, indicating stronger engagement consistency. H2 states that higher content quality is negatively associated with the CV of ER, indicating stronger engagement consistency.

Engagement consistency is positioned as a content-level signal of digital resilience because lower variability indicates a greater capacity of a content stream to reproduce audience response under changing platform and audience conditions, although such stability does not represent the full organizational meaning of digital resilience (Hokmabadi et al., 2024; Prasetya, 2026). H3 states that a lower CV of ER, indicating higher engagement consistency, functions as a meaningful content-level indicator of digital resilience for a local fashion brand. The scientific novelty lies in separating engagement magnitude from engagement consistency, operationalizing temporal engagement stability through the CV of ER, and examining content-level digital resilience through publicly observable TikTok behavioral data in a local fashion setting. Unlike studies centered primarily on individual-content performance, the framework evaluates whether audience response can be reproduced with sufficient regularity across time instead of interpreting episodic engagement peaks as evidence of sustainable digital performance (Xiao et al., 2023; Zhang et al., 2025; Salminen et al., 2024)).

Figure 1. Conceptual Framework of the Study



Lower Coefficient of Variation indicates higher engagement consistency.

Source: Developed from the cited theoretical and empirical literature.

Conceptually, the framework extends short-form video marketing analysis by connecting content attributes with temporal engagement regularity and extends digital resilience discussion through a deliberately bounded content-level performance indicator rather than a comprehensive measure of organizational resilience (Hokmabadi et al., 2024; Praselia, 2026). Practically, the framework enables local fashion businesses and digital marketing practitioners to distinguish repeatable audience response from isolated high-performing posts when evaluating short-form video strategy. Accordingly, the study aims to examine the relationships of brand storytelling and content quality with TikTok engagement consistency and to assess whether engagement consistency, operationalized inversely through the CV of ER, can serve as a meaningful content-level indicator of digital resilience in the TikTok activity of Eshnawn Studios.

3. Research Method

Research Design

This study applies a quantitative, non-reactive, secondary-data design within an exploratory single-case framework to examine the relationships of brand storytelling and content quality with TikTok engagement consistency. The single-case design is appropriate because the analytical purpose is to examine temporal content-performance patterns within the official TikTok account of one Indonesian local fashion brand rather than to estimate population parameters for the wider fashion industry. Publicly observable engagement metrics provide the behavioral data, while structured content analysis converts observable storytelling and content-quality attributes into coded measures.

Accordingly, the design supports analytical interpretation within the observed case but does not provide a basis for causal inference or statistical generalization across brands.

The study conceptualizes digital resilience narrowly at the content-performance level. Engagement consistency is therefore treated as an observable signal of whether audience responses remain relatively stable across successive content periods, rather than as a comprehensive measure of organizational resilience. This boundary is necessary because the dataset contains public TikTok content and engagement information but does not include managerial capabilities, financial performance, organizational routines, or internal adaptation processes. Consequently, all findings concerning digital resilience are interpreted as exploratory evidence of content-level stability within the observed digital communication environment.

Research Object, Data Coverage, and Unit of Analysis

The research object is the official TikTok account of Eshnawn Studios, @eshnawnstudios, an Indonesian local fashion brand that uses short-form video for digital brand communication. The population comprises all publicly accessible videos published from 22 June 2023 to 21 April 2026 that remained available at the time of data extraction. A video was included when complete public engagement information for views, likes, comments, shares, and saves was observable. Applying these criteria resulted in a final dataset of 40 eligible videos.

The 40 videos represent a census of the eligible content population within the defined account and observation window rather than a probabilistic sample drawn from a larger population. Their adequacy is therefore based on complete coverage of the eligible case material, not on a statistical sample-size threshold or power calculation. This distinction is important because the dataset is sufficient for describing and coding the observed content stream but is not intended to represent other local fashion brands, different TikTok accounts, or the broader population of short-form video marketing activities. The external representativeness of the findings is consequently bounded by the single-brand, single-platform, and time-specific design.

The individual video serves as the unit of observation because content attributes and engagement metrics are recorded for each published video. The observation period serves as the analytical unit for engagement consistency because the CV requires variation among multiple video-level ER values within a defined period. The 40 videos are grouped into six consecutive periods, with unequal numbers of videos reflecting the brand's naturally occurring posting activity rather than an experimentally balanced schedule. Accordingly, the 40 video-level observations provide the empirical material, while the six period-level observations determine the effective sample size for correlational and regression analyses.

Variables and Operationalization

Brand storytelling and content quality constitute the two coded content variables, while engagement consistency constitutes the focal outcome construct. Brand storytelling

captures the observable intensity of narrative framing through contextual, sequential, emotional, identity-related, symbolic, and product-integration cues. Content quality captures observable communicative and production characteristics including visual clarity, editing, message clarity, informational value, entertainment value, and overall brand coherence. Both variables are assessed through the five-point coding anchors reported in Table 1, which translate conceptual attributes into systematically observable content characteristics.

Video-level Engagement Rate (ER) is calculated from publicly visible audience reactions relative to views, while engagement consistency is operationalized inversely through the CV of ER within each observation period. A lower CV indicates that engagement rates are more closely distributed around their period mean, whereas a higher CV indicates greater variation among videos within the same period. The use of CV therefore separates the average magnitude of engagement from the regularity of engagement across repeated publications. This distinction prevents a period containing one unusually successful video from being automatically interpreted as consistently high-performing.

$$ER = [(Likes + Comments + Shares + Saves) / Views] \times 100$$

$$CV = \text{Standard Deviation of ER} / \text{Mean ER}$$

A negative association between a content antecedent and the CV indicates that higher values of the antecedent correspond with lower engagement variability and therefore stronger engagement consistency. Conversely, a positive association with the CV indicates that higher values of the antecedent correspond with greater engagement variability. The CV is not interpreted as engagement consistency itself but as an inverse empirical indicator of that construct. This interpretation is applied consistently in hypothesis evaluation and subsequent discussion of digital resilience.

Table 1. Operationalization of Research Variables

Variable	Role	Operational indicator	Scale and interpretation	Source
Brand storytelling	Independent variable	Structured coding of narrative intensity in each video	Five-point ordinal scale: 1 = plain product display with no clear narrative cue; 2 = product display with limited contextual cue; 3 = thematic framing around product use, style, or occasion; 4 = short narrative sequence connecting product, user situation, and brand meaning; 5 = emotionally driven or identity-based story where the product supports a broader narrative	Ben Aicha & Bouzaabia (2023); Prasetya & Benyamin (2026)
Content quality	Independent variable	Structured coding of communicative richness and production elaboration in each video	Five-point ordinal scale: 1 = minimal visual and informational element; 2 = simple product presentation with limited editing or message clarity; 3 = moderate elaboration with adequate visual clarity, caption, and product information; 4 = strong visual composition, editing, message clarity, and audience relevance; 5 = highly elaborated content combining visual quality, editing, information, entertainment, and brand coherence	Tian et al. (2022); Yu et al. (2024); Yudhyani & Sukirman (2025)

Variable	Role	Operational indicator	Scale and interpretation	Source
Engagement Rate	Video-level behavioral metric	Public reactions divided by views	Ratio scale expressed as a percentage, calculated from likes, comments, shares, saves, and views	Authors' computation
Coefficient of Variation of Engagement Rate	Empirical indicator of engagement consistency	Standard deviation of video engagement rates divided by mean engagement rate within each period	Ratio scale; lower value indicates higher engagement consistency	Authors' computation
Content-level digital resilience	Interpretive construct	Stability of engagement across repeated short-form video publications	Interpreted through lower engagement variability across periods, not through internal organizational capability data	Hokmabadi et al. (2024); Prasertia (2026)

Source: Authors' elaboration based on the cited literature and public TikTok data.

To clarify how the coding anchors were applied, a video presenting a product without an identifiable situation, narrative sequence, emotional cue, or identity-related meaning was assigned a low brand-storytelling score, while a video linking the product to a recognizable user situation, sequential action, and brand-related meaning received a higher score. For content quality, a video with limited visual elaboration, minimal product information, and little editing received a lower score, whereas content combining clear visual composition, coherent editing, understandable product information, audience relevance, and consistent brand presentation received a higher score. These illustrations describe the decision logic of the rubric rather than additional empirical categories and were used to maintain consistent interpretation of the five-point anchors across videos. Coding decisions were based only on observable video and caption characteristics and did not infer audience emotions, purchase motives, or other psychological states that were not directly available in the public data.

Data Collection and Coding Procedure

Data were collected through direct observation of the publicly accessible Eshnawn Studios TikTok account after the observation window ended on 21 April 2026. For every eligible video, a structured observation sheet recorded the publication date, caption, content theme, content type, views, likes, comments, shares, and saves. Public engagement metrics were captured at one fixed extraction point to improve comparability because displayed TikTok metrics may continue changing after publication. The same extraction procedure was applied to all eligible videos before period-level calculations were performed.

Structured content coding was conducted by one analyst using a written codebook derived from the operational definitions and five-point anchors reported in Table 1. Each video was examined together with its caption so that visual cues were interpreted within their observable communication context rather than as isolated images. Brand-storytelling

decisions considered situation, sequence, emotion-related presentation, identity cues, symbolic meaning, and product integration, while content-quality decisions considered visual clarity, editing, message clarity, informational value, entertainment value, and brand coherence. Scores were assigned only when the corresponding characteristics were observable in the video or caption.

A repeated-check procedure was applied to strengthen within-analyst consistency. After the initial coding pass, ambiguous or borderline cases were revisited against the written definitions and anchor descriptions, and the analyst compared the video, caption, assigned score, and documented rationale before the coding dataset was finalized. Audit notes were retained to document the basis for coding decisions and to reduce the risk that similar observable cues would be interpreted differently across videos. This process strengthened transparency and procedural consistency, although repeated checking by the same analyst cannot be treated as equivalent to independent intercoder agreement.

Formal intercoder reliability could not be calculated because the content dataset was coded by a single analyst rather than independently assessed by two or more coders. Intercoder reliability can strengthen the systematicity and transparency of a coding process when multiple coders are available, so its absence represents a limitation in the present measurement design rather than evidence that coder subjectivity was eliminated (O'Connor & Joffe, 2020). The codebook, explicit scoring anchors, repeated review of ambiguous cases, and retained audit notes were therefore used as procedural safeguards to constrain interpretive drift, but they do not substitute for formal intercoder reliability. The coded variables should consequently be interpreted as systematically structured single-analyst assessments whose reproducibility should be tested through independent multi-coder designs in future research.

Table 2. Data Collection, Coding, and Validation Protocol

Stage	Procedure	Output	Quality control
Account identification	Identify the official TikTok account and define the observation window	Public account and study period	Account handle, date range, and inclusion criteria documented
Video census	List all public videos from 22 June 2023 to 21 April 2026	Eligible video list	Videos excluded only when complete public metrics were unavailable
Metric extraction	Record views, likes, comments, shares, and saves	Raw engagement dataset	Metrics recorded at one fixed extraction point
Content coding	Score brand storytelling and content quality using the structured rubric	Video-level coded dataset	Decisions based only on observable video and caption attributes
Within-analyst review	Repeat review of ambiguous cases against the codebook, scoring anchors, video-caption context, and audit notes	Documented coding rationale	Single-analyst checking; not equivalent to formal intercoder reliability



Stage	Procedure	Output	Quality control
Period aggregation	Group videos into six periods and calculate period-level means and CV	Period-level analytical dataset	Formulas documented and spreadsheet retained as an audit trail
Statistical analysis	Apply descriptive statistics, Spearman correlation, supplementary Pearson correlation, exploratory regression, and sensitivity checks	Analytical results	Results bounded by the six period-level observations

Source: Authors' elaboration.

After video-level coding and metric extraction were finalized, ER was calculated for each video and the observations were grouped into six consecutive periods. Each period produced a mean storytelling score, mean content-quality score, mean ER, and CV of ER, thereby converting the video-level dataset into the period-level dataset required for evaluating engagement consistency. Period sizes were intentionally not equalized because the number of posts reflects the brand's actual publication behavior during each interval rather than an experimental posting schedule. Table 3 reports the temporal segmentation and number of videos contributing to each analytical period.

Table 3. Segmentation of the Observation Period

Period	Date Range	Number of Videos
P1	June 2023 to December 2023	12
P2	January 2024 to June 2024	4
P3	July 2024 to December 2024	9
P4	January 2025 to June 2025	7
P5	July 2025 to December 2025	5
P6	January 2026 to April 2026	3
Total	June 2023 to April 2026	40

Source: Authors' dataset compiled from public observation of the Eshnawn Studios TikTok account.

Data Analysis Technique

The analytical procedure combines descriptive statistics, correlation analysis, exploratory regression, and sensitivity checks. Descriptive statistics summarize storytelling, content quality, Engagement Rate (ER), and the Coefficient of Variation (CV) for each observation period and provide the primary basis for examining changes in engagement magnitude and stability over time. Spearman's rank-order correlation is used as the principal association measure because only six period-level observations are available and the antecedent measures originate from ordinal coding before aggregation.

Pearson correlation is retained only as a supplementary comparison of directional consistency under a linear association assumption.

Multiple linear regression is used solely as an exploratory supplementary analysis of the direction and combined explanatory pattern of brand storytelling and content quality in relation to the CV. With only six period-level observations and two predictors, the regression does not provide a sufficiently strong basis for population-level inference, stable parameter estimation, or causal interpretation. Regression coefficients and the coefficient of determination are therefore reported as descriptive exploratory evidence and are interpreted together with the correlation results and sensitivity checks. The study consequently emphasizes direction, pattern consistency, and case-specific interpretation rather than inferential certainty.

Hypothesis evaluation follows the inverse meaning of the CV. The first hypothesis is supported only when brand storytelling is negatively associated with the CV, while the second hypothesis requires a negative association between content quality and the CV because lower variability represents stronger engagement consistency. The third hypothesis is evaluated methodologically and descriptively by examining whether the CV meaningfully distinguishes periods characterized by relatively stable engagement from periods characterized by greater volatility. This procedure keeps the interpretation of each hypothesis aligned with its operational definition and prevents a positive relationship with variability from being incorrectly described as improved consistency.

Sensitivity checks address three specific vulnerabilities created by the small and uneven period-level dataset. The leave-one-period-out procedure examines whether the direction of an association is dependent on any single observation period, while the exclusion of the period with the highest CV evaluates sensitivity to unusually high engagement dispersion. A separate check excluding the shortest period examines whether the pattern is disproportionately influenced by the period containing the fewest videos. Period-size-weighted supplementary estimation then examines whether giving greater analytical weight to periods containing more videos materially changes the direction of the observed relationships.

These sensitivity analyses do not increase the underlying sample size and are not presented as substitutes for stronger statistical power. Their purpose is to determine whether the main directional patterns remain visible under reasonable alternative specifications of the six-period dataset. Results that remain directionally similar across these specifications can be regarded as less dependent on a single period, whereas changes in magnitude indicate sensitivity to period composition. All inferential statements are therefore bounded by the exploratory single-case design and the limited number of period-level observations.

4. Results and Discussion

Engagement Magnitude and Consistency Across Observation Periods

Across the 40 videos, the overall mean ER was 4.17 percent, which is close to the 4.20 percent TikTok engagement rate by views reported in a 2026 industry benchmark and is used only as broad context rather than a population standard (Cucu, 2026). Period-level results show that the aggregate average conceals substantial variation over time because mean ER ranged from 3.12 percent in P3 to 7.05 percent in P6, while the CV ranged from 0.231 to 0.596. This divergence demonstrates that engagement magnitude and engagement consistency provide different information about digital performance. Table 4 summarizes the period-level analytical results.

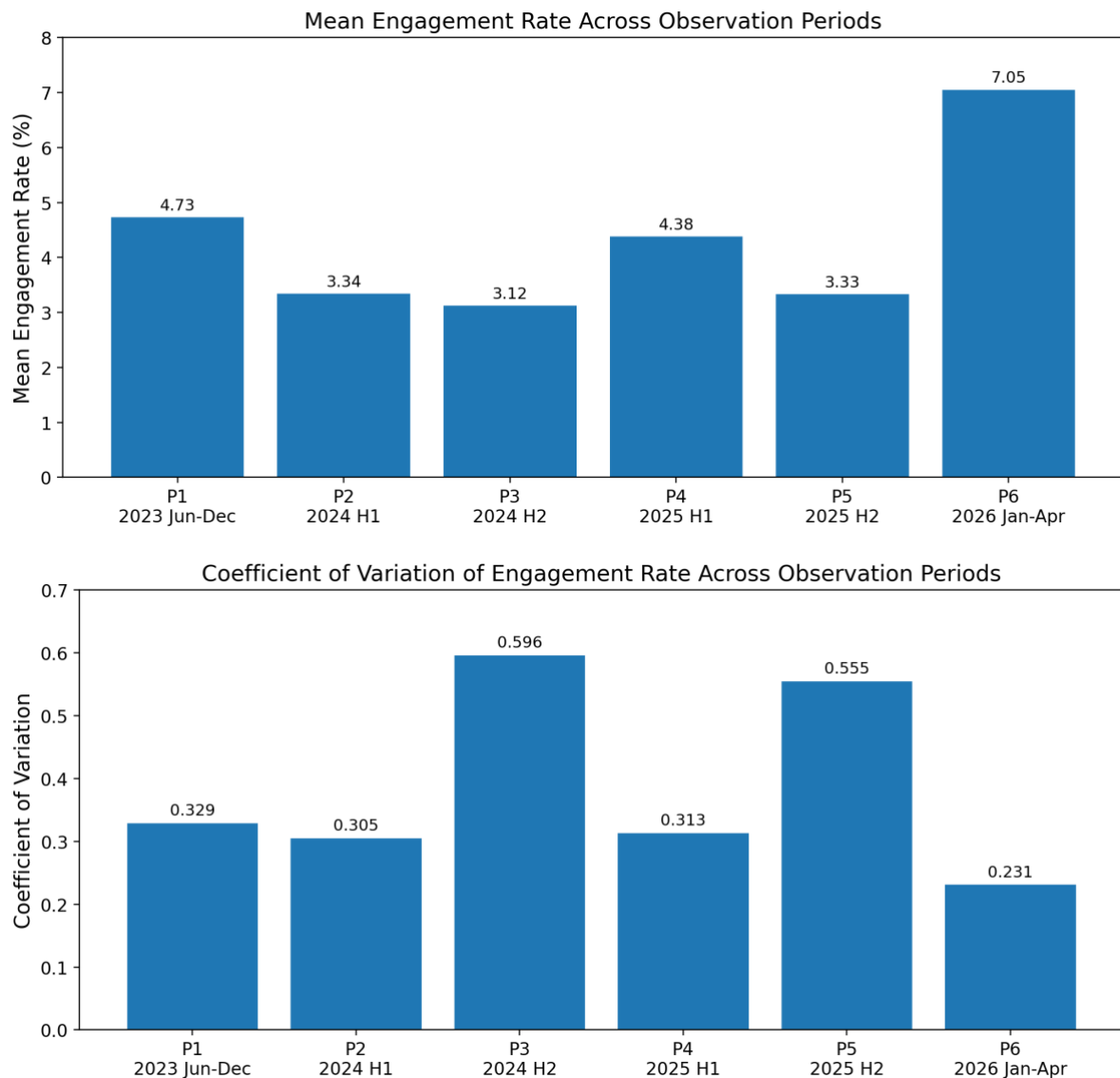
Table 4. Period-Level Analytical Results

Period	n	Mean Storytelling	Mean Content Quality	Mean ER (%)	CV of ER	Consistency Interpretation
P1 2023 Jun-Dec	12	2.75	2.50	4.73	0.329	Moderately stable
P2 2024 H1	4	2.75	3.00	3.34	0.305	Relatively stable
P3 2024 H2	9	3.00	3.67	3.12	0.596	Most volatile
P4 2025 H1	7	2.57	2.43	4.38	0.313	Relatively stable
P5 2025 H2	5	2.80	2.60	3.33	0.555	Volatile
P6 2026 Jan-Apr	3	2.00	2.00	7.05	0.231	Most consistent

Source: Authors' analysis of the Eshnawn Studios TikTok dataset.

P6 combines the highest mean ER with the lowest CV, whereas P3 combines the lowest mean ER with the highest CV. The contrast indicates that a period can perform strongly in average engagement while also differing substantially in the regularity of that engagement. P6 contains only three videos, so the low CV should be interpreted descriptively and not as evidence that a specific content style caused stability. Figure 2 visualizes the separation between engagement level and engagement variability across the six periods.

Figure 2. Mean Engagement Rate and Coefficient of Variation Across the Six Periods



Source: Authors' analysis of the Eshnawn Studios TikTok dataset.

Relationships of Storytelling and Content Quality with Engagement Variability

The association analysis follows the inverse interpretation of the CV. A positive coefficient indicates that a higher antecedent value is associated with greater engagement variability, whereas the theoretically expected direction for H1 and H2 is negative because lower CV represents stronger engagement consistency. Storytelling shows a strong positive Spearman association with the CV, while content quality shows a positive but statistically non-significant association. Table 5 presents the complete results and the supplementary linear estimates.

Table 5. Correlation and Exploratory Regression Results

Relationship	Coefficient	Significance or Note	Interpretation
Storytelling and CV, Spearman	$\rho = 0.899$	$p = 0.015$	Higher storytelling is associated with higher engagement variability
Content quality and CV, Spearman	$\rho = 0.657$	$p = 0.156$	Positive tendency toward higher variability, not statistically significant
Storytelling and CV, Pearson	$r = 0.744$	$p = 0.090$	Positive supplementary linear association
Content quality and CV, Pearson	$r = 0.705$	$p = 0.118$	Positive supplementary linear association
Regression of CV on both antecedents	$R^2 = 0.581$	$b(\text{storytelling}) = 0.220$; $b(\text{content quality}) = 0.075$	Exploratory model based on six period-level observations

Source: Authors' analysis.

H1 is not supported because storytelling is positively rather than negatively associated with the CV. The observed pattern means that periods with richer storytelling tended to exhibit greater dispersion in engagement, which differs from the expectation that narrative coherence would stabilize audience response. H2 is also not supported because content quality shows a positive and statistically non-significant association with the CV. The exploratory regression explains 58.1 percent of period-level variation in the CV, but the six-observation analytical base requires the model to be interpreted as directional case evidence rather than a stable predictive or causal model.

The counterintuitive storytelling result does not imply that storytelling is ineffective for digital marketing. A plausible interpretation is that richer narratives can create stronger responses to particular posts while producing weaker responses to other posts, thereby widening dispersion even when some individual content performs well. Short-form video engagement is known to vary with content characteristics, audiovisual features, and fragile early attention, so stronger narrative or production cues may increase episodic salience without guaranteeing repeated response across a content stream (Xiao et al., 2023; Zhang et al., 2025; Salminen et al., 2024). This interpretation separates the ability of content to attract attention from the ability of a brand to reproduce engagement consistently over time.

Platform distribution and audience composition provide additional contextual explanations that cannot be directly tested with the present dataset. TikTok recommendation processes may expose different videos to different audience pools, while content types can appeal unevenly across viewers with different interests and levels of prior brand familiarity. Because algorithmic allocation, viewer characteristics, watch-

time trajectories, and follower status were not available in the public dataset, these factors are treated as plausible unobserved influences rather than tested mediators. The positive association between storytelling and variability should therefore be interpreted as a case-specific temporal pattern that may reflect the interaction of content attributes with platform and audience conditions.

Sensitivity Analysis and Robustness Check

Sensitivity analysis was used to determine whether the observed direction depended excessively on one period, the highest-variability period, the shortest period, or the unequal number of videos across periods. The leave-one-period-out results keep the storytelling association positive across all exclusions, while the content-quality association remains positive but varies more substantially in magnitude. Excluding P3 or P6 weakens the content-quality relationship, and period-size-weighted estimates remain positive for both antecedents. Table 6 summarizes the alternative specifications.

Table 6. Sensitivity Analysis of Period-Level Associations

Sensitivity Specification	Treatment of Period Structure	Storytelling and CV	Content Quality and CV	Interpretation
Main Spearman correlation	All six periods retained	$\rho = 0.899$	$\rho = 0.657$	Positive direction in main model
Leave-one-period-out range	Each period excluded once	$\rho = 0.821$ to 1.000	$\rho = 0.400$ to 1.000	Positive direction remains across alternatives
Excluding P3	Highest-variability period excluded	$\rho = 0.821$	$\rho = 0.400$	Direction remains positive but weakens
Excluding P6	Shortest and most consistent period excluded	$\rho = 0.821$	$\rho = 0.400$	Direction remains positive after removing smallest period
Period-size-weighted Pearson	Number of videos used as period weight	$r = 0.742$	$r = 0.787$	Positive direction remains with unequal sizes considered
Period-size-weighted exploratory regression	Number of videos used as period weight	$b = 0.169$	$b = 0.134$	Weighted model remains positive; $R^2 = 0.657$

Source: Authors' recalculation from the period-level dataset.

The sensitivity checks strengthen confidence in the direction of the storytelling pattern because no single period reverses the association. The content-quality pattern is less stable in magnitude, which is consistent with its non-significant main correlation and indicates greater dependence on period composition. These checks do not compensate for

the small analytical sample and do not convert the results into confirmatory evidence. Their contribution is narrower: the positive directional pattern is not wholly attributable to one obvious period specification.

Engagement Consistency as a Content-Level Indicator of Digital Resilience

H3 receives methodological and exploratory support because the CV distinguishes periods with relatively stable engagement from periods with substantially greater volatility using only publicly observable behavioral data. This supports the use of engagement consistency as a content-level performance signal when digital resilience is defined narrowly as the stability of repeated content performance rather than as a complete organizational capability. The indicator adds information that mean engagement alone cannot provide because similar or even high average responses can coexist with very different levels of dispersion. This bounded interpretation is consistent with digital resilience literature that emphasizes sustained performance and adaptive capability while avoiding the stronger claim that public social media metrics capture organizational resilience in its entirety (Hokmabadi et al., 2024; Prasetya, 2026).

The distinction between magnitude and consistency extends short-form video research by shifting evaluation from the success of an individual post toward the regularity of response across a sequence of publications. Previous studies explain how content features influence engagement behavior, whereas the present case shows that content richness and engagement stability need not move in the same direction (Xiao et al., 2023; Zhang et al., 2025). The finding therefore refines the interpretation of strong content performance: a post or period can attract substantial attention without demonstrating a repeatable engagement pattern. Content-level digital resilience is better evaluated by considering both how much engagement occurs and how evenly that engagement is reproduced over time.

Practical Implications

For local fashion businesses, the findings suggest that content planning should separate experimentation for attention from routines designed for consistency. A practical content calendar can maintain recurring product-presentation, styling, usage-context, and customer-education formats as recognizable content pillars while reserving selected publication slots for richer story-led experiments. Rather than increasing storytelling intensity in every post, social media managers can compare the mean ER and CV across recurring periods to identify whether creative experiments raise attention without producing excessive instability. This approach converts engagement monitoring from a search for isolated viral peaks into a routine assessment of repeatability.

Content quality should likewise be managed as a repeatable communication standard rather than only as production elaboration. Clear product framing, readable information, coherent editing, and recognizable brand presentation can be standardized across recurring formats, while narrative complexity can be varied deliberately to test audience response. Periodic review of both average engagement and dispersion can help

identify whether a format consistently performs, whether a narrative experiment creates only an episodic spike, or whether a content pillar requires adjustment. Such a governance-oriented approach is consistent with the broader need for coordinated digital marketing strategy and data-informed performance management (Prasetia, 2026).

5. Conclusion and Suggestions

This study shows that engagement consistency provides information that is not captured by engagement magnitude alone in the TikTok activity of a local fashion brand. H1 is not supported because higher brand storytelling is associated with greater engagement variability, while H2 is not supported because content quality shows a positive but statistically non-significant relationship with variability. H3 receives methodological and exploratory support because the CV of ER distinguishes relatively stable periods from more volatile periods and therefore functions as a workable content-level indicator of digital resilience within the observed case. The principal contribution is the reframing of short-form video performance from isolated engagement peaks toward temporal regularity, while maintaining a clear boundary between content-level resilience and broader organizational resilience.

The findings remain bounded by an exploratory single-case design, 40 eligible videos from one TikTok account, six period-level analytical observations, unequal period sizes, and single-analyst content coding. These conditions limit statistical power, make the magnitude of associations sensitive to period composition, restrict external generalization beyond the observed brand and platform, and leave coding reproducibility untested by independent coders. Future research should include multiple fashion brands, longer observation windows, independent multi-coder assessment with formal reliability testing, and richer platform variables such as audience composition and distribution characteristics. Comparative studies across TikTok, Instagram Reels, and YouTube Shorts would also clarify whether the observed tension between content richness and engagement stability reflects a platform-specific pattern or a broader feature of short-form video marketing.

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