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Observed TikTok Interactions and Online Brand Search Interest: An Exploratory Six-Brand Study

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Abstract. Whether high engagement with brand posts accompanies broader search interest is difficult to establish from publicly visible platform counts. This exploratory study combines 381 retrospectively collected TikTok screenshot records for Chanel, Dior, Balenciaga, Nike, New Balance and Jaded London with worldwide Google Trends exports. Of the screenshot records, 364 have researcher-confirmed publication dates in April–September 2026. Daily Google Trends indices were averaged across 25 complete Sunday–Saturday weeks. The analysis includes 81 matched brand–week observations for five brands, Jaded London was excluded from linear regression because its search index was displayed as <1 throughout. An ordinary least-squares model with brand and week fixed effects estimates the association between within-brand standardized search interest and log mean cumulative interactions per captured post. The coefficient was −0.0264 (week-clustered standard error 0.0375, 95% confidence interval [−0.1037, 0.0510], p = 0.489). Alternative aggregation measures and selected sensitivity analyses did not produce a statistically significant association. The findings characterize the recorded sample, not all brand posts: capture coverage is unaudited, individual post IDs were not verified, and interaction counts accrued after publication. These constraints preclude causal interpretation and limit generalization. The study contributes a reproducible measurement example and identifies the challenges of aligning social-platform traces with search-interest data.

Keywords: cumulative interactions, Google Trends, luxury fashion, retrospective digital trace, fixed effects

1. Introduction

Fashion brands are evaluated using metrics that describe different actions. A TikTok like is an interaction with a particular post, a Google search may reflect product research, a runway collection, a celebrity, a scandal, or simple curiosity. Neither is an unambiguous measure of brand preference or purchase intention. Yet platform dashboards often encourage comparisons across exactly these metrics.

For luxury labels, the distinction is especially important. A brand's visual identity, cultural associations, and collaborations can generate broad conversation without producing immediate purchase decisions. Lifestyle and streetwear-oriented labels may similarly attract attention through product launches, communities, and collaborations. The practical question is therefore not whether

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social media "works" in general, but whether an observable measure of interactions with brand posts is systematically associated with a different observable measure of interest in those brands.

Earlier research links perceived social media marketing efforts with consumer-related outcomes, including luxury brand equity and customer responses [1, 2]. These studies generally examine constructs elicited from participants, rather than publicly displayed engagement counters. A visible count can offer a useful, reproducible trace of interaction with one post, but it does not identify why someone interacted, whether the interaction was favorable, or how the same person behaved on search platforms. This distinction motivates the empirical design.

The study examines Chanel, Dior, Balenciaga, Nike, New Balance and Jaded London over April–September 2026. It uses researcher-collected screenshots of brand-account posts and two worldwide Google Trends export batches. The first analysis describes the available six-brand TikTok sample. The second matches captured posts to the weekly mean of daily Google Trends indices and assesses the conditional association for the five brands with numeric search data.

The contribution is a carefully bounded empirical account rather than a claim about the overall effectiveness of social media marketing. The article documents a retrospective digital-trace workflow, quantifies the association within the observed sample, and shows how partial posting coverage, retrospective accumulation of engagement, and incompatible measurement scales limit what the analysis can establish. No age-cohort inference, causal effect, or sales outcome is estimated.

2. Literature review and analytical framework

2.1. Social media activity and consumer engagement

Kim and Ko [1] identify several dimensions of luxury fashion brands' social media marketing activity, including interaction and entertainment, and relate those dimensions to customer-equity outcomes. Godey and colleagues [2], studying luxury-brand consumers in several countries, also report links between perceived social media marketing efforts and brand equity and consumer responses. These findings motivate interest in digital channels, but neither establish that a larger publicly displayed like count on a particular post must coincide with higher search interest in that same week.

Engagement also has a broader theoretical meaning than behavioral clicks. Hollebeek, Glynn and Brodie [3] conceptualize consumer-brand engagement through cognitive, emotional, and behavioral dimensions. A sum of likes, comments, saves and shares captures only selected visible actions. It does not reveal whether those interactions were favorable, how much attention preceded them, or how many people saw the content. The study therefore calls this measure "observed cumulative interactions" rather than a comprehensive engagement rate or a psychological engagement scale.

Studies of influencer-mediated communications show that credibility, message value, and perceived closeness can affect responses to branded material [4, 5]. Abidin [6] describes visibility labor surrounding influencer fashion promotion, while Casaló and colleagues [7] examine perceived opinion leadership and behavioral intentions in a fashion-oriented Instagram setting. Vrontis and colleagues [8] synthesize the heterogeneous circumstances in which influencer marketing relates to consumer behavior. These studies provide context, but much of their evidence comes from Instagram, YouTube, or surveys. Their findings should not be treated as estimates for TikTok post-level counts in the present brands.

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2.2. Search interest as a separate signal

Search data have been used to examine changes in public attention, but a search-intensity index is not equivalent to the number of purchasers or to a direct measure of preference. Google Trends normalizes sampled search activity by place and time and reports a relative index between 0 and 100 [9]. It is therefore useful for observing variation within an explicitly defined query, geography, category, and window, while inappropriate for making unqualified claims about absolute brand popularity.

Evidence from marketing research also suggests that conversation content matters. Pauwels, Aksehirli, and Lackman [10] distinguish different types of electronic word of mouth and show that their relationships with online and offline responses can differ. For the present study, this implies that interactions with posts and brand search activity should be treated as potentially related but non-identical measures. A post may be popular because of an event or a personality rather than because consumers subsequently seek out the brand.

2.3. Brand context and hypotheses

Luxury consumption combines symbolic, social, personal, and functional dimensions [11], while luxury positioning may differ from mainstream brand-building approaches [12]. For descriptive purposes, the selected brands are grouped as luxury (Chanel, Dior, and Balenciaga) and streetwear/lifestyle (Nike, New Balance, and Jaded London). The labels are pragmatic groupings, not cleanly separated theoretical classes. This small purposive sample does not represent the population of all luxury, sportswear, or streetwear brands.

Two research questions guide the paper. RQ1: How do the observed cumulative TikTok interactions and screenshot coverage vary across the six brands? RQ2: Conditional on the availability of captured posts and numeric search indices, are weekly averages of observed per-post interactions associated with within-brand deviations in Google search interest after controlling for brand and calendar-week effects? The second question is exploratory. The available records do not support an experimental design, a post census, or a test of whether interaction preceded search.

3. Data and methods

3.1. TikTok screenshot observations

The TikTok data comprise 381 researcher-supplied screenshot records, with publication dates manually entered or corrected by the researcher. The four recorded platform-facing counts are likes, comments, saves, and shares. Video and image posts are pooled because their four recorded indicators are displayed in both formats. No product-category filter was applied: fashion, cosmetics, fragrance, cultural partnerships, and other content from the selected official-account material were eligible. Where the Jaded London material comprised menswear and womenswear account segments, those records were combined under one brand for summary statistics. Account-specific audience size was not available for normalization.

Of the 381 screenshot records, 364 carry recorded dates between 1 April and 30 September 2026, 17 fall outside this window. The dataset is not an independently checked inventory of unique TikTok posts: post URLs or identifiers and complete account posting histories were not established. We consequently describe the units as screenshots or captured-post records, not verified unique posts or all content published by the six brands. The author-confirmed manual dates serve as the study's

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working dates, but independent verification of the publication year for every post remains unavailable.

For screenshot record p, visible cumulative interactions are $I_p = Likes_p + Comments_p + Saves_p + Shares_p$. These components exclude views, impressions, and reach, the sum is not an engagement rate. For brand i and publication week t, the primary predictor is the logarithm of one plus the arithmetic mean of I_p among collected records attributed to that brand–week: $\ln[1 + \text{mean}(I_p)]$. This transformation reduces—but does not eliminate—the leverage of viral observations. The counts are retrospective snapshots as displayed at capture, they need not represent interactions that occurred during the indicated publication week. Values presented in abbreviated platform units may also be rounded.

3.2. Worldwide google trends series and alignment

The underlying Google Trends files report daily indices from 1 April through 12 October 2026. They identify the search geography as worldwide and the category as shopping. The present analysis restricts dates to April–September 2026, then computes the arithmetic mean of the daily indices for each complete Sunday–Saturday week. The 25 complete weeks begin on 5 April and end on 26 September 2026. A weekly mean of daily Google Trends indices is an analyst-constructed summary and need not equal a fresh weekly-frequency Google Trends export. The exact Google Trends search-surface setting was not independently established from the spreadsheet files and is not used to support a platform-specific claim.

The source indices come from two separate comparison batches: Chanel/Dior/Balenciaga and Nike/New Balance/Jaded London. Each Google Trends request uses its own 0–100 normalization. We therefore do not compare absolute index levels between those batches, nor infer relative search volume. For each brand with numeric readings, the 25 weekly means were standardized using that brand's mean and standard deviation over the same analysis weeks. The dependent variable is consequently a deviation in units of the brand's own weekly-index standard deviation. This transformation cannot make the underlying platforms, audiences, or search queries equivalent.

The Jaded London series is reported as "<1" on every observed day in the supplied Google Trends comparison. Such observations are censored below the displayed reporting threshold, they are not observed zeros. With no usable variation on the reported numeric scale, the brand is retained in descriptive TikTok summaries and the coverage figure but excluded from the conventional continuous-outcome regression. This is a limitation of the search measurement, not evidence that Jaded London attracted no searches.

3.3. Brand–week construction and missingness

The six-brand weekly layout contains 150 potential cells (six brands × 25 full weeks). A cell is eligible for engagement analysis only when at least one screenshot record is assigned to that brand–week. Absence from the screenshot collection is coded as unobserved coverage, not zero posting or zero engagement. Across the five brands with numeric Google Trends indices, 81 of 125 potential cells contain captured records and enter the regression, the remaining 44 do not supply an observed TikTok predictor. In total, 340 of the 364 in-period screenshots fall within the 25 complete weeks, of which 226 concern the five regression brands and 114 concern Jaded London. The regression is therefore conditional on a potentially selective capture process.

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3.4. Estimation and uncertainty

The principal specification is an ordinary least-squares model with brand and calendar-week fixed effects:

$$ZInterest_{it} = \alpha_i + \gamma_t + \beta ln(1 + MeanInteractions_{it}) + \varepsilon_i \quad (1)$$

The outcome $ZInterest_{it}$ is the standardized weekly mean of daily Google Trends indices. Brand intercepts α_i absorb observed brands' time-invariant differences and calendar-week indicators γ_t absorb shocks shared in the model sample during the same week. The coefficient β expresses a change in search-index standard-deviation units per one-unit change in ln(1 + mean cumulative interactions). It should not be read as an elasticity, a change in search volume, or the effect of TikTok activity on later searching.

The exploratory main specification uses standard errors clustered by week (25 calendar-week clusters), with a conventional small-sample correction and at t-reference distribution with 24 cluster degrees of freedom. Additional checks use HC3 robust standard errors, a model without week indicators, observed screenshot count as an additional regressor, mean/median/total interaction aggregations, exclusion of the most extreme 1% of captured post totals, and leave-one-brand-out fits. Week clustering allows cross-brand correlation within the same calendar week but does not fully address within-brand serial correlation, with only five regression brands and 81 selected cells, inferential uncertainty should be regarded as approximate. These are sensitivity analyses, not preregistered confirmatory tests.

4. Results

4.1. Observed TikTok sample

Table 1 describes only the screenshot records available to this study. Capture counts are largest for Jaded London and most geographically or temporally dispersed across the available weeks for several brands. Neither pattern measures the brands' actual posting frequencies: accounts, available archives, and researcher capture decisions were not independently audited. Cumulative interaction counts are highly right-skewed. The largest Chanel record contributes 51.9% of the interactions recorded for Chanel, illustrating why even per-post means may be dominated by a small number of unusually popular records.

Table 1. Descriptive statistics for observed TikTok screenshot records, April–September 2026

Brand	Records	Weeks with screenshots /25	Median interactions per record
Chanel	66	16	5,513
Dior	59	14	31,150
Balenciaga	41	20	2,108
Nike	42	15	4,818
New Balance	36	16	832
Jaded London	120	25	1,233

Note: Records are screenshots carrying researcher-confirmed working publication dates, not a verified census of unique official posts. The reported median uses likes + comments + saves + shares observed at capture, without normalization by views, account followers, or post age. Platform-abbreviated numbers may be approximate.

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Figure 1 shows that screenshot availability is uneven across brand–weeks. Empty cells are not evidence of inactivity, they indicate that no screenshot was recorded in the analytic collection for that cell. That distinction prevents an unsupported six-brand comparison of total publishing activity or campaign efficiency.

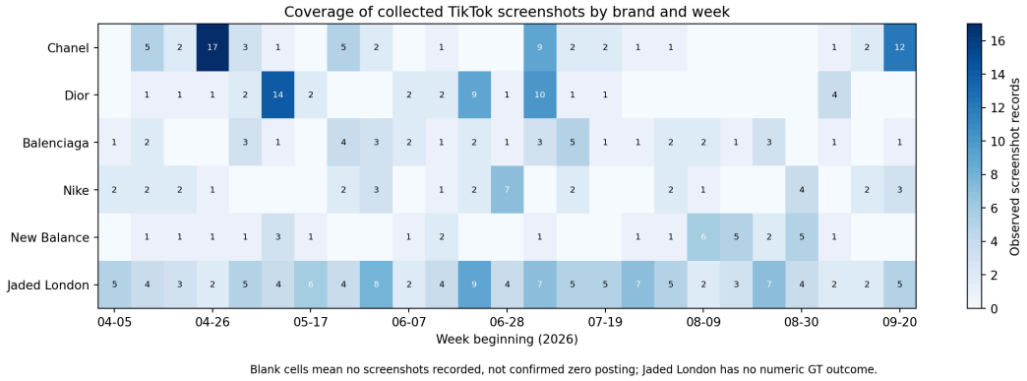


Figure 1. Number of captured TikTok screenshot records per brand and complete Sunday–Saturday week. A blank or zero cell indicates a missing record in the research collection, not verified non-publication

4.2. Matched brand–week regression

The primary two-way fixed-effects model uses 81 captured brand–week observations for Chanel, Dior, Balenciaga, Nike and New Balance. The coefficient on log mean cumulative interactions is −0.0264 (week-clustered SE=0.0375, 95% CI [−0.1037, 0.0510], p=0.489) (Table 2). Its confidence interval includes zero, and the coefficient is not statistically distinguishable from zero at conventional thresholds. This result provides no reliable evidence of a contemporaneous conditional association within the selected screenshot sample, it does not rule out associations in the universe of posts or effects measured on a genuinely aligned time scale.

The model's overall R^2 is 0.8868. Nearly all of that fit is attributable to the fixed-effect indicators: a model containing only brand and week effects has $R^2 = 0.8856$, so adding the TikTok predictor increases R^2 by only 0.0013. Reporting R^2 without that comparison would misleadingly attribute the fixed-effects fit to social media engagement. With brand effects but no week effects, the model R^2 is 0.0097, and the interaction term again is not significant.

Table 2. Exploratory regression of within-brand Google search interest on observed cumulative TikTok interactions

Specification	β	SE	p	95% CI	N
Brand + week fixed effects	−0.0264	0.0375	0.489	[−0.1037, 0.0510]	81
Same model, HC3 uncertainty	−0.0264	0.0406	0.519	[−0.1078, 0.0551]	81
Brand fixed effects only	−0.0227	0.0603	0.709	[−0.1471, 0.1017]	81
Control for observed post count	−0.0261	0.0389	0.509	[−0.1063, 0.0542]	81

Note: Dependent variable: per-brand standardized weekly mean of daily Google Trends Shopping indices. Main regressor: ln[1 + mean cumulative interactions among captured records assigned to that brand–week]. SEs are week-clustered except in the HC3 sensitivity row, intervals use the reported critical values. Results are conditional on captured weeks with numeric search measures and are exploratory, not causal.

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Figure 2 plots the predictor and outcome after residualizing both on brand and week effects, providing a visual check of the shallow conditional slope.

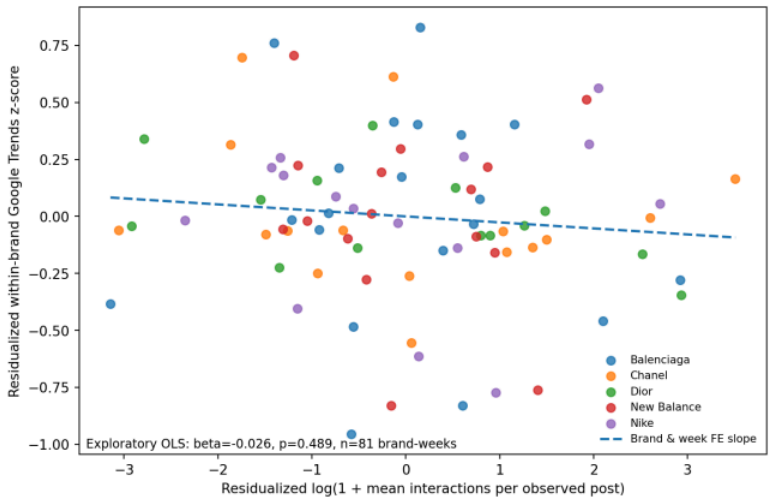


Figure 2. Partial regression plot after separately removing brand and calendar-week fixed effects from search interest and logged mean cumulative interactions (81 observed brand–weeks). The fitted line does not demonstrate a causal response

4.3. Sensitivity analyses

Sensitivity analyses did not reveal a statistically significant association under alternative definitions of observed engagement. Using median interactions per captured post produced β=−0.0336 (p=0.476), using total captured interactions produced β=−0.0225 (p=0.482). Adding the number of captured posts to the main model left the focal estimate essentially unchanged (β=−0.0261, p=0.509). Excluding the top 1% of captured posts by interaction count yielded β=−0.0311 (p=0.529, N=80 brand–weeks). None of these checks addresses unobserved posts, and a negative or positive coefficient in any of the models should not be treated as evidence of a causal relationship.

A leave-one-brand-out exercise also produced no conventionally significant association. Across the five four-brand models, the focal coefficient ranged from −0.0052 when Dior was omitted to −0.0440 when Nike was omitted, with p values ranging from 0.273 to 0.928. These analyses are intended to show sensitivity to the observed sample rather than to establish definitive robustness in a panel with so few brands (Table 3).

Table 3. Selected sensitivity results for the engagement coefficient

Alternative specification	β	p	N
Median per captured post	−0.0336	0.476	81
Total captured interactions	−0.0225	0.482	81
Exclude highest 1% of captured posts	−0.0311	0.529	80
Leave out Dior	−0.0052	0.928	67
Leave out Nike	−0.0440	0.273	66
Leave out Chanel	−0.0233	0.710	65
Leave out Balenciaga	−0.0249	0.465	61
Leave out New Balance	−0.0179	0.644	65

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Note: All specifications use the five-brand analysis framework, subject to the stated exclusion. The median, total, and top-1% analyses include brand and calendar-week fixed effects with week-clustered standard errors. Other leave-one-brand-out estimates are available in the accompanying analysis files.

The central empirical result is a failure to identify a statistically distinguishable contemporaneous association between the observed cumulative interactions on brand TikTok posts and relative Google search interest in this sample. That result matters precisely because a common analytical temptation is to use highly visible social media counts as a proxy for a broader marketing outcome. In these data, that substitution is not supported by the regression. The finding does not establish that engagement has no commercial value, nor does it contradict prior research relating richer social media constructs to brand equity [1-3]. The measures and research designs are different.

One substantive explanation for the weak estimated relationship is that engagement and search activity may be responses to different aspects of the same event. A campaign film, a runway show, or an appearance by a prominent individual can generate reactions inside TikTok without motivating a Google search. Conversely, consumers may search for product details before interacting with any official account. The direction of association may also depend on whether the post concerns a specific item, cultural event, or controversy. Studies of communication credibility and electronic word-of-mouth content reinforce the importance of such context [4, 5, 10]. However, this dataset does not contain validated content or sentiment categories capable of testing those mechanisms.

The managerial implication is limited but useful: visible post engagement and search-interest traces should be treated as complementary monitoring indicators, not interchangeable KPIs. Brands should not infer that a viral post raises general search demand, nor interpret a non-significant coefficient in this small selected sample as proof that engagement is unimportant. Likewise, the descriptive interaction medians are not performance rankings, as follower bases, content formats, post ages, and collection coverage differ.

5. Conclusion

This study examined 381 collected TikTok screenshot records from six brands alongside worldwide Google Trends data for April–September 2026. The descriptive dataset includes 364 in-period records. For the 25 complete weeks, the two-way fixed-effects analysis uses 81 eligible brand–week cells across five brands, Jaded London was excluded from linear regression because its available search-interest series was always reported as <1. The main conditional coefficient was −0.0264 ($p = 0.489$) and remained statistically non-significant under the reported sensitivity specifications. The findings do not establish a reliable contemporaneous link between retrospectively accumulated post interactions and brand search interest in this captured sample, and they cannot identify causality. Their principal contribution is to make the matching and measurement constraints explicit. The paper supports cautious use of digital metrics as complementary descriptive signals and shows which data improvements would be required before stronger cross-platform claims could be tested.

There are also some limitations. The main temporal limitation is that the predictor is assigned to the post's publication week, whereas likes, saves, shares and comments were recorded as cumulative values at a later screenshot date. The second major limitation is incomplete and potentially selective capture. Neither the number of posts published by each brand nor the uniqueness of every screenshot record has been independently confirmed. Third, the measures cover different audiences and domains. The TikTok indicators come from official-account screenshots with unknown viewers' countries and demographics, whereas Google Trends describes worldwide Google search behavior within the Shopping category. The TikTok sample deliberately contains all official content types, including non-shopping cultural posts, these may be especially poorly aligned with the restricted

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search category. In addition, within-brand standardization addresses scaling of the two export batches but does not equate absolute popularity or identify a common audience. Jaded London's <1 readings further restrict conclusions to five brands for regression.

A stronger study would require a documented inventory of official posts or a probability-based sample, persistent post identifiers, and consistently timed interaction snapshots. A matched measurement of the relevant audience geography and search definition would also improve interpretability. Further work should consider explicit modeling of low-index censored search observations and a larger brand panel.

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