Coherence Research

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Automotive & Motorcycle on TikTok Shop is growing against a falling market, and sales per view barely vary by creative choice

248 videos tracked, 132 analysed in depth, 100 top-selling products, 2 Sept–1 Oct 2026

Coherence Research

SCOPE
Category

DATA
2 Sept – 1 Oct 2026

SAMPLE
248 videos · 132 watched · 100 products · 1 category

KEY FINDINGS

01
+17.5%
revenue in the latest 4 weeks against the previous 4, while the market's 13-week revenue fell 11.1%

02
71.6%
of category revenue credited to affiliate creators

03
$32
revenue-weighted median price of top-selling products (middle half $15–$66)

04
1.37× and 1.41×
revenue per product in the $20–35 and $60–100 bands, against the average product

05
17.2%
of top-product revenue from products launched in the last 90 days

06
0.64
AUC of our model for top-selling videos (90% range 0.57–0.70)

ABSTRACT

We analysed Automotive & Motorcycle on TikTok Shop to see where sales happen, what sells at which price and commission, and which videos sell. Category revenue in the latest 4 weeks was 17.5% above the previous 4, while the whole market's latest 13 weeks were 11.1% below the previous 13. Sales are concentrated in the $20–35 and $60–100 bands, which sold about 1.4× the average product, and 71.6% of revenue is credited to affiliate creators. No hook or format differed reliably from the market average in sales per view, and our predictive model only modestly ranked top-selling videos (AUC 0.64). The sample is small and the window short, so findings are descriptive.

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1. Introduction

Automotive & Motorcycle is a practical, considered-purchase category, and brands and creators need to know whether it is worth investing in on TikTok Shop, at what price, and with what kind of video. Prior work on short-video popularity finds that attention is long-tailed, that early popularity predicts later popularity [1], and that creator features matter most in state-of-the-art prediction [2, 3]. That suggests creative choices on their own may explain little. Research on retail pricing [4], affiliate fees [5], live-stream selling [6] and long-tail online assortments [7] gives us reasons to look at price, commission, channel and competition alongside video style. We ask what the category's momentum, channels, prices, commission, competition, seasonality and video formats look like, and which patterns are strong enough to act on.

2. Data

Our analysis covers 2 September to 1 October 2026. We tracked 248 videos in the category, and our AI analyst watched and analysed 132 of them in depth. The marketplace figures rest on 100 top-selling products. Market-wide, 3,342 videos were watched, which provides the benchmark for sales per view.

Daily rankings of top-selling TikTok Shop videos in the US were collected from several independent sources and merged into one record per video. Where sources overlap, their sales estimates are cross-checked against each other, and videos whose estimates disagree by more than half are flagged. An AI analyst watched each video and recorded its opening, format, angle, production style, use of AI, hook source, length, pacing and what appears in the first second, without seeing how the video sold. Sales per view is a video group’s revenue per view divided by the market’s, shrunk toward the average for small groups, with 90% ranges. Weekly category figures for the US (estimated revenue, its split between video, LIVE and the shop tab, affiliate revenue, shops and active products, and a year of weekly revenue) and daily rankings of each category’s top-selling products (unit price, commission rate, launch date and revenue by channel) were collected from several independent sources. Medians of price and commission are weighted by revenue; momentum compares the latest weeks with the same number of weeks before. This paper covers 2026-09-02 to 2026-10-01: 248 videos tracked in Automotive & Motorcycle, 132 of

them watched and analysed; the market baseline uses all 3,342 watched videos; 100 top-selling products in Automotive & Motorcycle. Predictions come from a logistic model retrained daily and tested on recent weeks it had not seen.

3. Methods

Sales per view is a group of videos' revenue per view divided by the market's, shrunk toward the average for small groups by empirical Bayes [8], with 90% intervals on the log scale. A value of 1 is the market average. The predictive model is a logistic model of top-selling videos, retrained daily and tested on recent weeks it had not seen. We report AUC [9] with a bootstrap range [10].

4. Methods: marketplace measures

Momentum compares the category's estimated revenue in the latest 4 and 13 weeks with the same number of weeks before, using weekly revenue over the past year. Channels split latest-week revenue into shoppable video, LIVE and the shop tab. Prices, commission rates and product age are taken from the same top-selling products, with revenue-weighted medians and bands. Competition uses shops, active products, revenue per shop, the top ten's share and the Herfindahl–Hirschman index [11]. Seasonality compares each month with the category's average month, leaving out the partial first and last months; separating season from trend follows [12].

5. Results: momentum and sales channels

Automotive & Motorcycle accounted for 3.4% of revenue across all tracked categories in the latest 4 weeks, ranking 10th of 28. Its latest 4 weeks were 17.5% above the previous 4, and its latest 13 weeks were 4.9% above the previous 13. Over the same 13 weeks the market as a whole was 11.1% lower. The category is therefore growing against a weaker market, although the 13-week gain is modest.

In the latest week, 67.3% of category revenue came through shoppable video, 10% through LIVE and 22.7% through the shop tab. The market splits 64.9%, 17.1% and 18%. The category leans slightly more on video and the shop tab and less on LIVE. LIVE selling is associated with trust-building in social commerce [6], so the smaller LIVE share may be an unused channel, though we cannot tell from these data. Affiliate creators were credited with 71.6% of revenue.

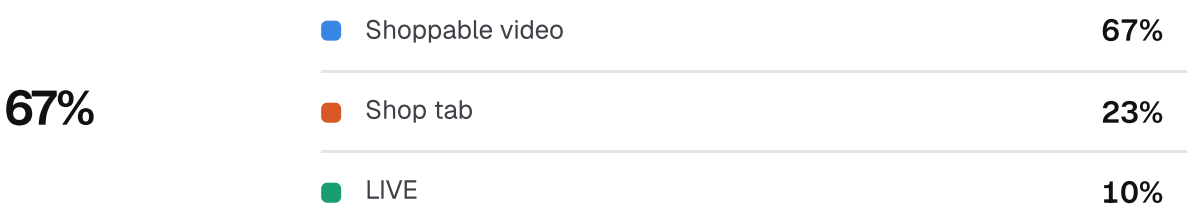

Figure 1. Automotive & Motorcycle: where sales happen (latest week). Source: ContentIQ analysis of 248 TikTok Shop videos, 2 Sept – 1 Oct 2026.

6. Results: prices, commission, product age and competition

The revenue-weighted median price of top-selling products is $32, with the middle half between $15 and $66. Products at $20–35 (16 products, 21.9% of revenue) and $60–100 (13 products, 18.3%) earned 1.37× and 1.41× the average product. The $10–20 band holds the most products (31) and 23.8% of revenue, but each earned 0.77× the average. Under $10 earned 0.79× and $100 and over 0.88×.

The revenue-weighted median commission is 8%. Products paying 5–10% (46 products) took 56.2% of revenue at 1.08× the average product, and 10–15% (35 products) took 35.7% at 0.9×. Higher commission was not associated with higher revenue per product. The 15–20% band has only 3 products, so we do not interpret it. Products launched in the last 90 days make up 17.2% of top-product revenue, and products aged 1–2 years hold 41.5% (1.19× the average), so newcomers can break in but established products dominate.

The category has 7,070 shops and 40,358 active products. Average revenue per shop is $1,546, against $2,401 in the median category, which has 4,461 shops. The top ten products take 31.9% of top-product revenue, the same as the median category, and the Herfindahl–Hirschman index is 232, which indicates low concentration among the tracked products. Many shops share the revenue, but no small group of products dominates.

Table 1. Automotive & Motorcycle: top-selling products by price band.

Band	Products (n)	Share of revenue	Revenue per product vs average
Under $10	12	9.5%	0.79×
$10–20	31	23.8%	0.77×
$20–35	16	21.9%	1.37×
$35–60	15	15%	1.00×
$60–100	13	18.3%	1.41×
$100 and over	13	11.4%	0.88×

Note. Among the top-selling products we track in the latest week; revenue per product is against the average product in the same set (1.00 = average). Source: ContentIQ analysis of 248 TikTok Shop videos, 2 Sept – 1 Oct 2026.

7. Results: which videos sell

Among hooks, none differed reliably from the market average. Price or deal hooks had the highest point estimate at 1.23× (90% range 0.88–1.71), but this rests on 6 videos and our confidence is low. Relatable POV was 1.12× (0.66–1.89, 10 videos). Bold claim, the most common hook (26 videos,

20.1% of watched-video sales), was 1.02× (0.77–1.33). Visual pattern-break was lowest at 0.87× (0.58–1.31). Every range includes 1.

Demo or tutorial was the dominant format, with 93 videos and 83.7% of sales, at 0.99× (0.84–1.17, high confidence). Other formats have 5 to 9 videos each and wide ranges, such as skits at 1.12× (0.49–2.56). Filmed live action accounted for all of the production sales, at 0.99× (0.82–1.21).

Our model for top-selling videos reached an AUC of 0.641 (90% range 0.573–0.696) on 2,667 training rows. It was not trained only on analyses that never saw sales (cleanOnly is false), so its features may partly reflect sales knowledge, and we treat it as weak evidence. Its strongest signals were filmed live action (odds ratio 2.54) and no visible AI (1.71).

Table 2. Sales per view and share of sales by hook.

Value	Videos (n)	Share of sales	Sales per view	90% range
Price or deal	6	4.3%	1.23×	0.88–1.71
Relatable POV	10	10%	1.12×	0.66–1.89
Question	7	4.3%	1.05×	0.68–1.62
Straight into the demo	14	15.2%	1.05×	0.73–1.51
Test or challenge	6	4.9%	1.03×	0.74–1.44
Bold claim	26	20.1%	1.01×	0.77–1.33
Comparison	5	3.9%	0.96×	0.64–1.46
Problem call-out	25	17.2%	0.93×	0.66–1.32
Visual pattern-break	18	20.1%	0.87×	0.58–1.31

Note. Sales per view is relative to the market (1.00 = average), shrunk toward the average for small groups (empirical Bayes); ranges are 90% intervals on the log scale. Source: ContentIQ analysis of 248 TikTok Shop videos, 2 Sept – 1 Oct 2026.

8. Discussion

For brands, the evidence points to price and product choice rather than hook choice. The $20–35 and $60–100 bands earned the most per product, the $10–20 band was crowded, and high commission was not associated with higher revenue. Competition is wide but not concentrated, which leaves room for new products. For creators, demonstrating the product on filmed footage is the norm, and sales per view in this category barely depend on hook or format. Distribution, creator reach and the product itself may matter more, as prior work suggests [2].

Alternative explanations apply. The strong growth may reflect a few products or a recovery from a weak earlier period. Price bands may reflect product type rather than price. Affiliate-credited revenue is observational, and the returns to advertising are hard to measure from such data [13]. Boosting with ads appears in the model, but we cannot separate it from product quality.

Seasonally, the category's past year ranged from 0.78× a normal month in January to 1.35× in June, with November at 1.08× and December at 1.11×. Halloween is under way, Black Friday / Cyber Monday starts in 40 days, holiday gifting in 45 and New Year resolutions in 92. The history covers fewer than a full year and shows only a modest lift into the holiday months, so we would not treat the calendar as a strong guide.

Figure 2. Automotive & Motorcycle: monthly sales against its own average month (1 = a normal month). Source: ContentIQ analysis of 248 TikTok Shop videos, 2 Sept – 1 Oct 2026.

9. Limitations

Most videos in the sample are top-ranked, so findings mostly separate strong sellers from good ones rather than from all videos; typical and weak videos are being added. Product figures cover the top-selling products we track in each category, not every listing, so they describe what sells best rather than everything on sale. Results are associations, not causes. Paid promotion, creator audience size and product price are not fully controlled for. Revenue, views and sales are estimates, not figures reported by TikTok. The window is one month, only 132 videos were analysed in depth, and many hook and format groups have fewer than 10 videos, so their ranges are wide. Marketplace figures rest on 100 top-selling products and do not describe the long tail. The seasonal history covers about ten months, so it cannot separate season from trend. The predictive model was not trained only on analyses that never saw sales. All findings are associations.

10. Conclusion

Automotive & Motorcycle on TikTok Shop is growing faster than the market, sells mostly through affiliate-driven video, and rewards mid-priced products ($20–35 and $60–100) more than cheap or premium ones. Hook and format show no reliable difference in sales per view, and our model's predictive power is modest. Brands should test price points and product range first, and creators should focus on clear demonstrations. These are associations from a short window and a small sample, and they should be re-tested as more data arrive.

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