

Platform Heterogeneity in Creator-Driven Brand Engagement: A Matched-Brand Comparison of Bilibili and Rednote

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Abstract. Cross-platform brand research typically collapses distinct engagement actions into single metrics and overlooks heterogeneity in brand presence. This research examines whether there is a difference in promotional engagement between Bilibili and Rednote, and whether the platform gap varies across likes, comments, and shares. Using 3,833 promotional posts by 191 brands active on both platforms in July 2025, this study controls for creator follower count, brand fixed effects, and publication-date fixed effects through log-linear regressions and uses HC3 heteroskedasticity-robust standard errors. The fully adjusted results show that Rednote's expected engagement was lower than on Bilibili by 47.1% for likes, 56.9% for comments, 43.7% for shares, and 48.5% for total engagement. The platform penalty is sharpest for comments; like and share gaps are statistically indistinguishable. Follower count was positively correlated with engagement, but elasticities of 0.39 to 0.49 indicated that the increase in engagement was lower than the growth of follower size. The robustness test did not change the direction of the platform differences, but after reweighting, it reduced the influence of brands that posted frequently on one platform, narrowing the sharing gap. These findings support platform-specific engagement benchmarks, KPI design aligned with promotion objectives, and more disciplined creator pricing.

Keywords: Platform Affordances, Creator-driven Promotion, Engagement Decomposition, Cross-platform Benchmarking

1. Introduction

1.1. Research context and practical relevance

The rapid digitization of daily life has repositioned social media as the primary touchpoint between consumers and commercial information. Nowadays, social media platforms have become essential channels for brands to communicate with consumers, disseminate product information, and build online communities. According to the China Internet Network Information Center, China's online population stood at 1.108 billion by December 2024, with an internet penetration rate of 78.6% [1].

This near-ubiquitous connectivity renders digital platforms indispensable for brand visibility and customer acquisition. In this vast digital market, Bilibili and Rednote have become widely popular platforms for brand content. As of mid-2025, both platforms reached comparable scales, with Bilibili averaging 363 million monthly active users (MAUs) in Q2 and Rednote reporting approximately 350 million MAUs in August, establishing them as parallel arenas for branded content distribution [2, 3]. The huge scale of users and active creators makes them important channels for brand promotion.

In view of this, it is necessary to clarify whether the differences in likes, comments, and shares across platforms have a significant practical necessity and research value. At the level of commercial value, different interactive behaviors correspond to different promotion goals such as brand exposure, consumer discussion, and secondary dissemination of content. Examining each behavior separately can help brands choose performance indicators that align with activity goals rather than relying solely on total engagement. For example, campaigns aimed at enhancing content recognition and increasing brand exposure may place greater emphasis on likes; activities designed to collect consumer feedback and enhance user participation can focus on comment performance; and those seeking to expand the scope of content dissemination may pay more attention to shared performance. Furthermore, controlling creator follower counts helps distinguish platform differences and provides a more reasonable basis for brands to choose creators.

1.2. Literature review

Extant research grounded in platform affordance theory demonstrates that structural and normative differences across social media architectures systematically shape user interaction patterns. Shen compared 9,330 brand posts published by 10 brands across Twitter, Instagram, and TikTok and found significant platform differences in likes and comments [4]. This research further points out that, compared to simply changing the content strategy across platforms, it is more important to select the right platform. User engagement should also be viewed as a multidimensional concept. Analyzing news content on Facebook, Tenenboim established that liking, commenting, and sharing constitute theoretically distinct modes of engagement, each responding to unique content features [5]. This underscores the need to disaggregate engagement metrics rather than treating them as interchangeable indicators. The creator's own characteristics may also affect the interaction obtained by promoting content. Tafesse and Wood found that on Instagram, the number of influencer followers is negatively correlated with engagement per post per follower, suggesting that a larger audience size does not necessarily bring about a proportional increase in engagement [6]. In the context of the Chinese platform, Sun, Zhou, and Yang analyzed approximately 30,000 Bilibili videos and found that the relationships among sponsored content, sponsored disclosure, and consumer engagement varied with influencers' popularity [7].

Based on the above literature, while many scholars have primarily studied differences in interactions on Facebook, Instagram, Twitter, and TikTok, direct comparisons across major Chinese social platforms remain lacking. Some studies suffer from limitations such as focusing only on a single brand or a few product categories, or using samples from different periods with inconsistent brand composition. In addition, many studies have combined multiple user interactions into a single comprehensive indicator, thereby ignoring the commercially significant differences among likes, comments, and shares. Therefore, it is still necessary to match and compare the promotional content involving the same group of brands on Bilibili and Rednote. The comparison can reduce interference from brand composition, estimate platform gaps of different types of interaction, formally test

whether these gaps vary across interactive behaviors, and evaluate whether the conclusions remain stable under different samples and weighting methods.

1.3. Research objectives and analytical framework

To fill the gap in the above research, this study compares the promotional posts published on Bilibili and Rednote from July 2 to July 31, 2025. Only the posts corresponding to the brands that appear on both platforms are retained. This research treats likes, comments, and shares as dependent variables, with total engagement as a supplementary indicator. Platform is the core explanatory variable, with creator follower count, brand, and publication date included as controls. Accordingly, this study pursues three interrelated research questions:

RQ1: After controlling for creator follower count, brand fixed effects, and publication-date fixed effects, do Bilibili and Rednote differ systematically in likes, comments, shares, and aggregate engagement?

RQ2: Does the magnitude of platform difference vary across specific engagement types?

RQ3: Are these platform gaps robust to alternative model specifications and sampling criteria?

2. Method

2.1. Data source and sample construction

This study draws on a publicly available post-level dataset archived on Mendeley, originally compiled to examine how influencers' sharing motivations affect brand interaction intention [8]. The dataset offers a consistent coding scheme across platforms, making it well-suited for cross-platform comparative analysis. The study selected two files: Study 1a (Bilibili: com-data) and Study 1b (Rednote-data). The two original documents contain 9,975 Bilibili observations from July 2025 and 79,566 Rednote observations from January to July 2025. To ensure time comparability, this research retains only posts published between July 2 and 31, 2025.

The unit of analysis is the individual creator-generated promotional post. Key variables include platform identifier, brand name, publication date, creator follower count, and three engagement metrics: likes, comments, and shares. Data processing removed exact duplicate records, records with missing key variables, and negative observation count variables. Brand names are standardized by harmonizing character formats, deleting unnecessary spaces, and merging confirmed brand aliases. Only identical brand names were treated as the same brand. Finally, this study restricted the sample to brands appearing on both platforms, yielding a matched-brand dataset of 3,833 promotional posts (2,337 from Bilibili; 1,496 from Rednote) across 191 common brands.

2.2. Variables, model specification and estimation strategy

This study uses the number of likes, comments, and shares to measure different forms of user interaction and sums these indicators to obtain the total amount of interaction as a supplementary dependent variable. Since the engagement measures and the number of fans were strongly right-skewed, this research adopts $\ln(x + 1)$ transformation for relevant variables, which preserves zero-valued observations and reduces the influence of extremely large values. To isolate platform effects, this study estimates a series of ordinary least squares (OLS) regressions with incremental inclusion of covariates: creator follower count, brand fixed effects, and publication-date fixed effects. The model settings were as follows:

$$\ln(Y_i + 1) = \beta_0 + \beta_1 P_i + \beta_2 \ln(F_i + 1) + \alpha_{b(i)} + \delta_{t(i)} + \varepsilon_i \quad (1)$$

where Y_i denotes likes, comments, shares, or total engagement obtained by the post i ; P_i is the platform indicator; F_i is the number of creator followers; $\alpha_{b(i)}$ and $\delta_{t(i)}$ represent the brand and publication-date fixed effects, respectively. Bilibili was coded as 0 and Rednote as 1, so β_1 indicates the difference between Rednote and Bilibili after controlling for relevant factors. The platform coefficients were further converted into percentage differences through $100 \times [\exp(\beta_1) - 1]$. The main regression used HC3 heteroskedasticity-robust standard errors.

To test whether the platform gap varied across engagement types, this study established a stacked regression model. Robustness checks included standard errors clustered by anonymized creator IDs; the sample was limited to 1669 posts from 30 brands that appear at least five times on both platforms; winsorization of follower count and the four engagement measures at the 1st and 99th percentiles; and weighted least squares regression using the reciprocal of the number of posts in each brand-platform combination as the weight. All analyses were conducted in Python using pandas, NumPy, and statsmodels.

3. Empirical results

Bilibili was coded as 0 and Rednote as 1, so the negative platform coefficient indicates a lower expected interaction volume of Rednote after controlling for the established factors. Since the dependent variables were all transformed as $\ln(x + 1)$, platform coefficients are converted into percentage differences by $100 \times [\exp(\beta_1) - 1]$.

3.1. Descriptive evidence and econometric estimates

3.1.1. Sample composition and univariate distributions

The final matching sample comprised 3,833 creator-generated promotional posts from 191 brands that appeared on both platforms simultaneously. Among them, there are 2,337 posts on Bilibili and 1,496 on Rednote, both released between July 2 and 31, 2025.

Table 1. Descriptive statistics of Bilibili and Rednote

Measure	Bilibili Mean	Bilibili Median	Rednote Mean	Rednote Median
Likes	12,933.70	1,477.0	1,831.44	1,100.5
Comments	457.18	58.0	82.89	42.0
Shares	623.30	24.0	139.87	26.0
Total engagement	14,014.18	1,702.0	2,054.19	1,191.5
Followers	322,293.66	55,326.0	120,679.11	51,129.5

Table 1 shows that the average number of likes, comments, shares, and total engagements for Bilibili posts was higher than for Rednote posts. Mean total engagement was 14,014.18 on Bilibili and 2,054.19 on Rednote. However, all engagement means were significantly higher than the median, indicating strongly right-skewed distributions. The difference in the number of shares is particularly obvious: Rednote had a slightly higher median than Bilibili (26 versus 24), whereas Bilibili's mean was much higher than Rednote's (623.30 versus 139.87). Follower counts were also uneven. Bilibili had 322,293.66 mean followers, and Rednote had 120,679.11, while the

corresponding medians were relatively close at 55,326 and 51,129.5, respectively. These descriptive disparities underscore the importance of controlling for brand heterogeneity and creator follower count when comparing cross-platform performance.

3.1.2. Main estimates: platform effects on engagement

The step-by-step model shows that the platform coefficients became statistically significant after including brand fixed effects. When the platform was the only predictor, the platform coefficients for likes, shares, and total engagements were relatively small and statistically insignificant; only comments showed that Rednote was significantly lower by 27.0%. Adding follower count did not substantially change the overall pattern. However, after adding brand fixed effects, all four platform coefficients became negative and significant: -47.7% for likes, -57.0% for comments, -43.7% for shares, and -48.9% for total engagement. When the publication-date fixed effects were added, the coefficient only changed slightly. This shows that the main platform difference came from comparisons that held brand identity constant, rather than from the direct comparison of the two platforms.

As shown in Table 2 and visualized in Figure 1, Rednote records significantly lower engagement across all metrics ($p < .001$). The platform gap is most pronounced for comments (-56.9%), followed by total engagement (-48.5%), likes (-47.1%), and shares (-43.7%). All 95% confidence intervals lie strictly below zero, indicating robust platform effects.

Table 2. Fully adjusted fixed-effects estimates

Outcome	Platform β (HC3 SE)	95% CI	Difference (%)	Followers β (HC3 SE)	Followers p	Adjusted R^2
Likes	-0.637*** (0.090)	[-0.814, -0.460]	-47.1%	0.489*** (0.020)	< .001	0.679
Comments	-0.843*** (0.086)	[-1.012, -0.673]	-56.9%	0.394*** (0.017)	< .001	0.526
Shares	-0.575*** (0.102)	[-0.775, -0.375]	-43.7%	0.425*** (0.020)	< .001	0.498
Total Engagement	-0.663*** (0.089)	[-0.837, -0.489]	-48.5%	0.477*** (0.019)	< .001	0.672

Note. Percentage difference = $100 \times [\exp(\beta) - 1]$. *** $p < .001$.

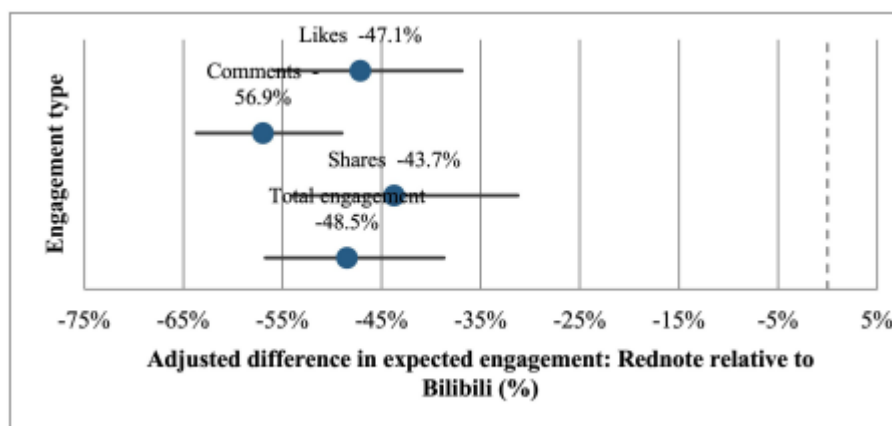


Figure 1. Adjusted Rednote–Bilibili differences across engagement measures

Note. Points show $100 \times [\exp(\beta) - 1]$ for Rednote relative to Bilibili; horizontal lines show transformed 95% confidence intervals.

Creator follower count was significantly positively correlated with the four results (all $p < .001$). The coefficients ranged from 0.394 for comments to 0.489 for likes, and the coefficients of shares and total engagement models were 0.425 and 0.477, respectively. Consistent with prior evidence of diminishing returns to scale, follower count exhibits positive but inelastic associations with engagement (elasticities ranging from 0.39 to 0.49), indicating that a 1% increase in audience size yields a smaller proportional increase in interactions. Adjusted R-squared values ranged from 0.498 for shares to 0.679 for likes, while the total engagement model reached 0.672.

3.1.3. Heterogeneity in platform gaps across engagement types

This research further adopted a stacked model with standard errors clustered by the original post to formally test differences in the platform coefficients for likes, comments, and shares, while allowing the follower, brand, and date effects to vary by engagement type. The likes coefficient was significantly less negative than the comments coefficient (coefficient difference = 0.205, SE = 0.065, $p = .0016$, 95% CI [0.078, 0.333]). The comments coefficient was also significantly more negative than the shares coefficient (difference = -0.268, SE = 0.070, $p < .001$, 95% CI [-0.405, -0.131]). In contrast, there was no significant difference in the platform coefficient for likes and shares (difference = -0.063, SE = 0.064, $p = .330$, 95% CI [-0.188, 0.063]). Therefore, the evidence supports a distinctly larger platform gap for comments, but it cannot prove that the platform gap between likes and shares is different.

3.1.4. Robustness checks and sensitivity analyses

The main direction was retained across four robustness checks. First, according to the clustering standard errors across 2,925 anonymized creators, the statistical inference was nearly unchanged, and all platform coefficients remained significant at $p < .001$. Second, after restricting the analysis to 1,669 posts from 30 brands that had at least five posts on each platform, the coefficients remained significantly negative. In this sub-sample, the percentage difference ranged from 47.9% for likes to 62.7% for comments. Third, winsorizing follower count and engagement measures at the 1st and 99th percentiles yielded estimated results close to the main model; for example, the total interaction coefficient changed only from -0.663 to -0.659.

Finally, after weighting each post by the inverse of the number of posts in the brand-platform unit, the absolute values of the four coefficients decreased, but each remained statistically significant. The difference in the number of shares was the largest: the coefficient changed from -0.575 to -0.358, while the corresponding difference reduced from 43.7% to 30.1% ($p = .018$). The weighted differences between likes, comments, and total engagement were 43.4%, 46.8%, and 44.0%, respectively. In general, the direction of platform association did not depend on a particular standard-error calculation, extreme values, or the brand-platform cells with the largest number of posts. Nevertheless, the magnitude of the share gap was more sensitive to brand-platform weighting.

3.2. Interpretation of key empirical patterns

3.2.1. The limits of aggregate engagement metrics

Total engagement suggested that Rednote was 48.5% lower, but this single measure concealed a significantly larger 56.9% difference in comments. By comparison, there was no significant

difference between the platform gap of likes and shares. Relying solely on total engagement masks substantial heterogeneity across interaction types. Most critically, the pronounced deficit in Rednote comments (−56.9%) implies that platforms perceived as equivalent based on aggregate metrics may, in fact, underperform on dimensions vital to soliciting consumer feedback and fostering public dialogue.

3.2.2. Platform-specific benchmarking and influencer evaluation

The adjusted gaps showed that all types of engagement on Rednote were 43.7%-56.9% lower than on Bilibili. In addition, although follower count was positively associated with engagement, the increase in engagement was smaller than the increase in followers. Adopting identical interaction targets for Bilibili and Rednote, or evaluating creators primarily by the number of fans, may therefore misjudge promotional performance. The results indicate that when defining performance benchmarks, it is necessary to distinguish engagement types. Furthermore, creators should not be evaluated solely on follower count, as engagement increases less than proportionally with audience size.

3.2.3. Endogenous brand composition and resource allocation

The platform coefficients only changed significantly after the brand fixed effect was added, and the estimated share difference narrowed under brand-platform weighting. Therefore, the overall average performance of the platform not only reflects differences between platforms but is also affected by the composition of high-frequency posting brands. Using pooled averages as a universal budget rule may be misleading. Before allocating resources, enterprises still need to use cross-platform data of their own brands for verification.

4. Discussion: from metric design to strategic allocation

Through in-depth analysis of matched brand samples from Bilibili and Rednote, this study reveals systemic differences in user interaction behavior across cross-platform promotion. In particular, by further elaborating on the three core problems identified in Section 3.2, this section aims to explain why aggregate indicators will mask behavioral differences, why a unified KPI will lead to evaluation deviations, and why the platform mean will mislead resource allocation.

4.1. Beyond aggregate engagement: the comment penalty

Total engagement can easily summarize the overall observable response, but it can conceal differences in specific interaction behaviors. The total engagement gap of 48.5% is less than the 56.9% comment gap but larger than the 43.7% share gap. Therefore, analyzing only aggregate indicators will obscure platform gaps in comments and shares. Chang and Wu found that likes and comments of promotional posts were not related to the product-centredness of comment content [9]. This result shows that the number of interactions cannot fully capture users' specific responses. Moran et al. demonstrated that consumer engagement behaviors with Facebook brand content varied across marketer-controlled stimuli [10]. These findings jointly support the analysis of engagement behaviors separately.

The descriptive composition results further support this explanation. Although the absolute numbers of comments and shares for Rednote are low, the proportion of each in total engagement is slightly higher. A higher proportion within a smaller total should not be interpreted as stronger

performance. Brands can keep total engagement as an overall indicator, but when the promotion goal involves visible recognition, feedback, discussion, or redistribution, it should evaluate likes, comments, and shares separately. Otherwise, a favorable-looking composition may conceal weak absolute participation.

4.2. Platform-specific performance standards

The estimated gap between different types of engagement is inconsistent, so applying a single cross-platform KPI may lead to misleading performance evaluations. If the two platforms adopt identical comment or share targets, Rednote promotional campaigns may be evaluated against unified benchmarks that are not supported by the estimated results of the common brand sample, resulting in unreasonable performance comparison between platforms. The higher interaction baseline for Bilibili should not be taken as greater marketing value, because this study measures visible engagement, not sales or conversions. Lou et al. showed that platform characteristics and affordances shape influencer-follower relationships and advertising outcomes [11]. Furthermore, Dvir-Gvirsman et al. found that perceived platform affordances affect the reception and dissemination of content [12]. These studies reinforce the value of platform-specific performance standards.

Therefore, brands can establish platform-by-engagement benchmarks and evaluate creators against the relevant platform standards, rather than comparing raw cross-platform interaction counts directly. The evaluation target should also be aligned with the purpose of promotion: likes reflect visible reactions with a low participation threshold, comments enable discussion and feedback, shares enable redistribution, and total engagement captures overall visible response. In practice, managers can set sub-platform targets based on their past performance, and consider these estimates alongside content quality, conversion, and cost when reviewing promotional activities or budgets. This method helps prevent creators from being overvalued or platforms from receiving excessive budget allocation solely because of higher observable interaction levels.

4.3. Brand mix sensitivity in resource decisions

By matching on common brands and controlling for brand fixed effects, this study overcomes the limitations of a simple platform-average comparison. The WLS results narrowed the estimated share gap from 43.7% to 30.1%, indicating that, in the unweighted post-level estimates, brands with more posts on a particular platform had a greater impact on the results. Therefore, the 43.7% share gap depends on the distribution of posts in the current sample and should not be treated as universal. For campaigns with sharing as the main goal, relying only on unweighted results may overstate the expected platform difference and misdirect posts or budgets.

Before allocating resources, brands should compare unweighted and WLS estimates and explain them alongside their posting frequency, promotion goals, creator mix, and historical performance. The unweighted model summarizes all observed posts in the current sample, and WLS indicates whether the results are sensitive to high-frequency brand-platform combinations. Managers can use the overall estimate as an initial reference, calibrate it against past campaigns or a small pilot, and then adjust resource allocation. Since the share gap under WLS remained at 30.1%, the direction did not change, but the gap was sensitive to the distribution of postings; therefore, 43.7% should not be used directly as a fixed prediction multiplier.

5. Conclusion

5.1. Summary of findings

Across 191 brands and nearly 4,000 creator promotions, Rednote generates systematically lower interaction volumes than Bilibili, with the gap most acute for comment-based dialogue rather than passive likes or redistributive shares. Follower count was positively correlated with engagement, but elasticities of 0.39 to 0.49 indicated that the increase in engagement was lower than the growth in follower count. Although the direction of platform differences remained stable after robustness tests, reducing the influence of brands that posted frequently on one platform narrowed the sharing gap.

5.2. Managerial implications

This research shows that cross-platform comparison needs to consider platform differences and interaction types. When evaluating the creators of the two platforms, brands should not adopt the same interaction target, but should set reference standards for likes, comments, and shares on each platform to reduce misjudgment caused by different platform baselines. In addition, common brand matching and reweighting can test whether the estimated platform differences are affected by the uneven posting frequency. Examining the three measures separately also helps managers select KPIs based on campaign priorities rather than relying solely on total engagement. By comparing unweighted and reweighted results, managers can be more cautious in budget allocation and creator pricing without assuming that platform averages apply equally to every brand. Finally, if the fan volume elasticity is less than 1, it means that a larger follower base does not yield the same proportional increase in interaction. Therefore, when choosing creators, expected engagement gains and collaboration costs should also be considered, not just by follower count.

5.3. Scope and future research

This study has three main limitations. First, the one-month observational data cannot establish a causal relationship or show whether the platform difference persists. Second, although retaining only common brands improves comparability, the research results may not apply to brands that are promoted only on a single platform. Third, engagement counts cannot reflect content characteristics, paid exposure, promotion costs, and sales conversion. Future research can extend the observation period and incorporate brands with different cross-platform activity patterns, while integrating indicators of content, exposure, cost, and conversion. On this basis, Longitudinal or quasi-experimental designs can further test whether platform differences are stable and identify which content, creators, or platform characteristics explain these differences.

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