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Endorsement Rate in Influencer Marketing

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Abstract

Influencer marketing has emerged as a prevalent marketing strategy for firms seeking to engage target customers, with significant research identifying various criteria for influencer selection. However, the role of endorsement rate—the proportion of an influencer's brand-sponsored posts relative to their total social media posts—remains underexplored. This study addresses this gap by investigating how influencers' endorsement rates affect the effectiveness of their subsequent sponsored posts. Using a multimethod approach, including two field studies and two controlled experiments across diverse platform contexts (e.g., Instagram, Twitter, Douyin), the findings reveal a consistent U-shaped relationship between endorsement rate and consumer engagement with sponsored posts. This pattern arises from the interplay of two countervailing forces: A higher endorsement rate enhances the influencer's perceived brand recognition, yet it simultaneously raises audience suspicion of manipulative intent. Notably, organic product mentions and consistent brand endorsements can attenuate the impact of endorsement rates on consumer engagement. Beyond advancing research in influencer marketing and brand endorsements, these findings offer marketers a valuable framework for evaluating influencers and making more informed selections.

Keywords

endorsement rate, online influencers, influencer marketing, consumer engagement, social media

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In influencer marketing, firms incentivize online influencers to create and share brand-specific content on social media (Leung, Gu, and Palmatier 2022). Expenditures on this critical marketing tactic are projected to reach U.S. $32.55 billion by 2025 (Statista 2025), enabling firms to amplify their brand visibility, improve brand perceptions, and strengthen consumer relationships (Hughes, Swaminathan, and Brooks 2019). Influencers vary in their content focus, ranging from those who primarily endorse products to those who mostly share personal stories. Thus, they can be distinguished by their endorsement rate—the proportion of brand-sponsored posts to total social media posts. A common recommendation suggests avoiding partnerships with influencers who have high endorsement rates, citing the possibility that excessive sponsored content alienates followers and undermines the influencer's subsequent effectiveness (Garnès 2019). Yet real-world market observations also suggest that influencers with high endorsement rates continue to sustain strong consumer engagement and offer substantial value to brands (Ritschel 2018). Such discrepancies motivate the current research, which aims to specify how influencers' endorsement rates actually affect consumer perceptions and campaign outcomes.

We address three research questions: (RQ1) How does an influencer's endorsement rate affect sponsored post engagement? (RQ2) What mechanisms underlie this impact? and (RQ3) How do an influencer's past content strategies, for both sponsored and organic posts, moderate the impact of endorsement rate? The findings reveal an intriguing U-shaped relationship between an influencer's endorsement rate and engagement levels in sponsored posts, a pattern that might result from the interplay of two countervailing forces. Higher endorsement rates may signal an influencer's brand recognition, or the extent to which the influencer is acknowledged and validated

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in the brand marketplace (Rapp et al. 2015), but they also may raise perceptions of manipulative intent, such that consumers believe the influencer is attempting to persuade them using manipulative means (Campbell 1995; Cotte, Coulter, and Moore 2005).

Building on these dual mechanisms, we identify boundary conditions that shape the effect of endorsement rate on sponsored post engagement. First, "organic product mentions" refer to how often influencers mention products of the same type as the focal sponsored product in their prior organic posts. Frequent mentions of similar products signal influencers' genuine interest and knowledge in that domain. When consumers encounter endorsements for such products, their concerns about manipulative intent, related to the influencers' endorsement rate, may be mitigated. Second, "brand endorsement consistency" reflects the extent to which an influencer has repeatedly endorsed the same brand as the focal sponsored brand in previous sponsored posts. This consistency reduces the perceived diversity of the influencer's brand associations and may weaken the positive effect of endorsement rate on perceived brand recognition.

Using a multimethod approach—including two field studies and two controlled experiments—we identify a U-shaped relationship between endorsement rate and sponsored post engagement, while also specifying the boundary conditions. In doing so, we make several theoretical and managerial contributions. First, prior studies have explored various influencer traits, such as expertise, follower count, and followee count (Hughes, Swaminathan, and Brooks 2019; Leung et al. 2022; Valsesia, Proserpio, and Nunes 2020; Wies, Bleier, and Edeling 2023). This research enriches the influencer marketing literature by focusing on endorsement rate, an understudied characteristic with effects that remain ambiguous. Some recent studies touch on related concepts, such as influencers' overall posting activity (Leung et al. 2022), the number of prior sponsorships (Beichert et al. 2024; Wies, Bleier, and Edeling 2023), and sponsorship disclosure (Cao and Belo 2023). However, none of these studies consider the broader context of an influencer's profile to examine how the *proportion* of sponsored content relative to total posts affects consumer perceptions of influencers and their endorsements.

Second, our findings challenge a conventional view in the celebrity endorsement literature that increasing endorsement activity leads to a linear decline in effectiveness due to negative distinctiveness and credibility effects (Mowen and Brown 1981; Tripp, Jensen, and Carlson 1994). These studies find that endorsing a greater number of products, compared with a single product, reduces consumer attitudes, without exploring potential nonlinear effects. In contrast, the U-shaped relationship between endorsement rate and sponsored post engagement reflects two countervailing mechanisms: perceived brand recognition and manipulative intent. By illustrating the complex, dual impacts of endorsement rate, our findings emphasize its concurrent positive and negative effects on engagement. We also respond to calls by Haans, Pieters, and He (2016) for deeper investigations of U-shaped dynamics in strategic marketing.

Third, we demonstrate that both organic product mentions and brand endorsement consistency moderate the effects of endorsement rate through their impacts on the countervailing mechanisms. The results offer practical guidance for firms in selecting influencers and for influencers in optimizing their content strategies. Influencers who frequently discuss a particular product type organically have more flexibility in accepting sponsorships for similar products, as their displayed genuine interest helps mitigate perceptions of manipulative intent. Conversely, influencers who repeatedly endorse the same brands may face diminishing returns from perceived brand recognition, as consistent endorsements fail to translate into broader industry recognition. Therefore, when selecting influencers, marketers should consider both their endorsement rates and content history to identify the most effective collaborations.

Conceptual Background

In influencer marketing, "engagement" refers to measurable behaviors that consumers exhibit in response to influencer-generated content, such as liking, commenting, or reposting (Leung et al. 2022). These behaviors are significantly affected by key attributes of the influencer, such as attractiveness, expertise, and trustworthiness (Hughes, Swaminathan, and Brooks 2019; Lou and Yuan 2019), as well as observable metrics like follower count (Beichert et al. 2024; Gu, Zhang, and Kannan 2024; Leung et al. 2022; Wies, Bleier, and Edeling 2023) and followee count (Valsesia, Proserpio, and Nunes 2020).

We propose that engagement also depends on another relevant and observable influencer trait: the endorsement rate, defined as the proportion of brand-sponsored posts relative to the total number of posts shared on a social media platform. Influencers typically share a mix of organic content and brand-sponsored posts, making the endorsement rate a unique and easily observable trait for consumers. This visibility is crucial for shaping consumers' perceptions and their likelihood of engaging with sponsored posts; the quantifiability of the endorsement rate also makes it a practical and actionable criterion for firms when selecting influencers.

Although the impacts of endorsement rate on engagement with sponsored posts remain underexplored in influencer marketing research, some related concepts have been investigated (see Table 1 for a summary). For example, an influencer's overall posting activity offers a holistic measure of the influencer's activity level (Leung et al. 2022), without differentiating sponsored versus organic posts. Studies on sponsorship disclosure also outline the consequences of such disclosures but may overlook the cumulative impacts of influencers' past endorsement activities on consumer perceptions (Cao and Belo 2023; Karagür et al. 2022).

Furthermore, some studies incorporate the influencer's prior endorsements as a control variable, though these analyses yield inconclusive findings. For example, Beichert et al. (2024) identify a negative effect of sponsored postings on follower engagement and revenue. Wies, Bleier, and Edeling (2023) find insignificant effects of the number of prior sponsored posts (normalized by the number of days the influencer's account has been

Table 1. Selected Studies on Concepts Related to Endorsement Rate.

Research	Context	Concept	Operationalization	Method	Mechanism	Findings Related to the Concept
Posting Activity						
Leung et al. (2022)	Influencer marketing	Influencer activity	Total number of posts an influencer publishes on social media	Field study (Sina Weibo)	—	Influencer activity has an inverted U-shaped impact on influencer marketing effectiveness.
Stephen et al. (2017)	Social media	Transmitter activity	Average number of social media posts per day	Field studies (Twitter, LiveJournal); experiments	Perception that the content is fresh or current	Transmitter activity on social media has a positive impact on aggregate-level content propagation.
Sponsorship Disclosure						
Cao and Belo (2023)	Influencer marketing	Explicit sponsorship disclosure	Header tag "paid partnership with" on the top of the post	Field studies (Facebook, Instagram); online experiments	Advertising awareness; sponsorship transparency	Explicitly disclosing sponsorship increases user engagement, driven by increased information transparency about the sponsorship.
Ershov, He, and Seiler (2025)	Influencer marketing	Sponsorship disclosure	Hashtags with "#ad" or "#sponsored"	Field study (Twitter)	—	• Shares of nondisclosed content decline slightly over time. • Nondisclosed posts tend to originate from younger brands with a large Twitter following and from smaller influencers with greater engagement per follower.
Prior Endorsements						
Beichert et al. (2024)	Influencer marketing	Sponsored posting	Number of sponsored postings by an influencer	Field studies (Instagram)	—	Sponsored posting has a significant negative impact on revenue per follower.
Wies, Bleier, and Edeling (2023)	Influencer marketing	Prior sponsored posts	Number of prior sponsored content, normalized by the days the influencer's account is active	Field study (Instagram); experiments	—	The number of prior sponsored posts has insignificant effects on engagement.
Yang, Zhang, and Zhang (2025)	Influencer marketing	Video ads influencer has posted	Number of video ads an influencer has posted	Field studies (TikTok, Taobao)	—	The number of video ads posted by an influencer has insignificant effects on sales lifts.
Number of Endorsements						
Knoll and Matthes (2017)	Celebrity endorsement	Endorsement rate	Human coding of endorsement rate on a ten-point scale	Meta-analysis	Attitude toward ad; attitude toward object	Endorsement rate does not have a significant impact on endorsement effectiveness.
Rice, Kelting, and Lutz (2012)	Celebrity endorsement	Multiple brand endorsements	Number of brands endorsed by a celebrity (manipulation)	Experiment	—	In low involvement conditions, brand attitudes become more negative if a celebrity endorses multiple brands.
Tripp, Jensen, and Carlson (1994)	Celebrity endorsement	Number of endorsed products	Number of products endorsed by a celebrity (manipulation)	Experiment	Celebrity credibility	• The number of products endorsed by the celebrity reduces consumers' perception of celebrity credibility and likability, ad evaluations, and purchase intention. • The effects depend on the number of celebrity exposures.
Endorsement Rate						
This article	Influencer marketing	Endorsement rate	The proportion of brand-sponsored posts relative to the total number of posts shared on a social media platform	Field studies (Instagram and Douyin); experiments (Twitter and Instagram)	Perceived brand recognition; perceived manipulative intent	• Influencers' endorsement rate has a U-shaped impact on sponsored post engagement, mediated by perceived brand recognition and perceived manipulative intent. • Organic product mentions and brand endorsement consistency weaken the U-shaped impact.

active) on both post and story engagement, while also controlling for prior total posts. Although these analyses touch on the logic behind the endorsement rate, they measure prior endorsements by the number of sponsored posts, without directly considering their proportion relative to the influencer's total number of posts. In other words, they do not address the mix of sponsored and organic posts. Yet in reality, consumers form perceptions based on the overall composition of the influencer's content, not just the number of sponsored posts (Garnès 2019). Capturing the actual mix of organic and sponsored content offers a novel perspective on how consumers develop perceptions of influencers, which in turn likely affects their engagement with sponsored posts.

Prior research on celebrity endorsement has examined how the number of products or brands endorsed by a celebrity affects consumers' attitudes toward advertising and purchase intentions. The findings generally suggest a negative linear or insignificant effect, attributed to diluted credibility (Rice, Kelting, and Lutz 2012) and reduced endorser–product distinctiveness (Mowen and Brown 1981). However, to the best of our knowledge, these studies have not yet explored potential nonlinear effects. Unlike traditional celebrities, influencers create and share both sponsored and organic content, making the endorsement rate a uniquely relevant feature. In the dynamic influencer landscape, influencers adopt varying endorsement rates: Some focus primarily on organic content, whereas others mostly offer product endorsements (Mardon, Cocker, and Daunt 2023). These differences highlight the need to better understand how variations in endorsement rates shape consumer perceptions and responses.

Hypothesis Development

To develop our hypotheses, we integrate insights from both in-depth interviews and the existing literature. Specifically, we employed the theories-in-use approach (Zeithaml et al. 2020) and conducted 12 interviews with influencers from diverse domains and representatives from influencer marketing agencies. These interviews provided valuable insights that informed our theoretical development, enabling us to extend existing perspectives on endorsement rates and clarify the nomological net of relationships among the constructs in our framework (Zeithaml et al. 2020). To substantiate our hypotheses and their underlying logic, we incorporate quotes from the interviews into the hypothesis development (see Web Appendix A for details).

Effect of Endorsement Rate on Sponsored Post Engagement

We predict that endorsement rate has a U-shaped effect on sponsored post engagement. We propose that this pattern reflects the increasing benefit of perceived brand recognition, which follows a convex curve, and the increasing cost of perceived manipulative intent, which follows a concave curve. We illustrate this U-shaped effect and the additive combination of the two latent mechanisms in Web Appendix B (Haans, Pieters, and He 2016).

The prevalence of influencers as professional endorsers suggests potential benefits of frequent endorsements. In particular, a higher endorsement rate should enhance an influencer's perceived brand recognition—the extent to which consumers believe the influencer is acknowledged and validated in the brand marketplace (Rapp et al. 2015). This perception reflects consumers' beliefs that brands recognize and validate the influencer's value (Drori and Honig 2013; Rao, Chandy, and Prabhu 2008). An influencer–brand collaboration represents a strategic alliance between an influencer and a sponsoring brand (Leung et al. 2022); when brands partner with a particular influencer, it affirms the latter's marketplace visibility and commercial value (Drori and Honig 2013). As an influencer (Interviewee 1) shared, "Influencers with a high proportion of endorsements demonstrate their market capability and are valued by brands." Unlike celebrities, who possess established fame, influencers typically lack formal institutional recognition (Leung, Gu, and Palmatier 2022), but they can rely on brand recognition to achieve a form of industry validation or seal of approval (Cheng and Zhang 2024).

A low endorsement rate may appear sporadic or incidental, such that it cannot signify brand recognition, but a moderate rate helps position the influencer as an emerging industry player, even if their brand recognition is still developing. In contrast, a high endorsement rate signals strong demand and widespread recognition (Rao, Chandy, and Prabhu 2008). As one influencer (Interviewee 5) noted, "When I started taking on many endorsements, [my followers] saw it as a validation of my hard work by the market and felt proud of me." At this stage, the benefits of frequent endorsement may accelerate, as it reinforces the influencer's broad industry acceptance and marketplace position (Wiley 2022), supporting the expectation of a convex benefit curve. This aligns with the exponential growth model of fame, according to which recognition increases exponentially with achievement due to the heightened visibility and salience of repeated successes (Simkin and Roychowdhury 2013). When enhanced perceptions of brand recognition strengthen the influencer's external legitimacy (Rao, Chandy, and Prabhu 2008), it boosts consumer engagement with their sponsored posts.

Nevertheless, prior studies of celebrity endorsements identify negative impacts of endorsing multiple brands (Mowen and Brown 1981; Tripp, Jensen, and Carlson 1994). Accordingly, we also posit that frequent endorsements by influencers may evoke negative perceptions of manipulative intent, defined as consumer inferences that the influencer is attempting to persuade them by manipulative means (Campbell 1995) and is driven by commercial motives (Cotte, Coulter, and Moore 2005). Influencers with low endorsement rates are often perceived as organic content creators, evoking little suspicion of manipulative intent (Chung, Ding, and Kalra 2023). However, at moderate endorsement rates, influencers appear to deviate from organic sharing norms, creating ambiguity in content focus that heightens audience skepticism about their commercial intentions. As one influencer (Interviewee 5) shared, "If an influencer starts doing endorsements, the audience often feels quite resentful because they are used to reading about the influencer's life. … When people see it's an ad, they immediately think, 'Are you just doing this for the money? Are you just trying to profit off me by promoting this?'"

At higher endorsement rates, however, the increase in perceived manipulative intent becomes more gradual. Influencers with high endorsement rates are typically viewed as professional endorsers, whose commercial intent is expected and accepted (Mardon, Cocker, and Daunt 2023). This perspective aligns with the idea of suspension of disbelief in advertising (Stern 1994), where consumers accept marketing as legitimate and persuasive if it fulfills its intended purpose (Deighton, Romer, and McQueen 1989). One influencer we interviewed, who posts only sponsored content (Interviewee 1), explained, "Once we became more commercialized, our audience started to anticipate when an ad might appear. … They've gotten used to it, so it's no longer a big deal. … My followers are happy to see sponsored content; they even expect it!" Thus, at high endorsement rates, perceptions of manipulative intent plateau, as the influencer's commercial role becomes an accepted norm. As perceptions of manipulative intent rise steeply at low to moderate endorsement rates and then level off at higher rates, a concave cost curve likely emerges.

Combining the convex benefit of perceived brand recognition and the concave cost of perceived manipulative intent, we propose a U-shaped relationship between endorsement rate and sponsored post engagement. At low to moderate endorsement rates, influencers seem to lack sufficient brand recognition while suspicions of manipulative intent rise sharply, resulting in reduced engagement. As the endorsement rate reaches higher levels, influencers establish themselves as recognized professional endorsers, which outweighs lingering skepticism, leading to increased sponsored post engagement. In summary, we hypothesize:

> **H_1:** An influencer's endorsement rate exhibits a U-shaped relationship with sponsored post engagement.

> **H_2:** An influencer's endorsement rate affects sponsored post engagement by (a) increasing perceived brand recognition, which amplifies post engagement, and (b) increasing perceived manipulative intent, which diminishes post engagement.

Boundary Conditions of the Endorsement Rate Effect

Consumers' perceptions of influencers, according to their endorsement rates, vary with the context, which includes the influencers' historical organic and sponsored content. We propose that two contextual boundary conditions alter the impact of endorsement rate on sponsored post engagement: organic product mentions and brand endorsement consistency.

"Organic product mentions" refer to how often influencers mention products of the same type as the focal sponsored product in their earlier organic posts. Consider an influencer endorsing a beauty product. If they have frequently discussed beauty products in their previous organic posts, they exhibit a high level of organic product mentions. This may attenuate the U-shaped impact of endorsement rate on sponsored post engagement by reducing consumers' perceptions of manipulative intent associated with frequent endorsements. Frequent organic discussions indicate the influencer's genuine interest in the product type, irrespective of commercial influences (Morhart et al. 2015). As an influencer (Interviewee 8) mentioned, "I mainly focus on sharing food content because it feels more genuine. I just enjoy food and capturing nice photos of it. It doesn't matter whether restaurants invite me or not. I just keep doing what I enjoy." For influencers with high endorsement rates, endorsements that align with their typical organic content appear to offer natural extensions of their existing interests (Bansal and Voyer 2000). As a beauty and lifestyle influencer (Interviewee 2) explained, "The brands [I have endorsed] align pretty well with my personal image and vibe. For my followers, these brands might actually be helpful … and could make them more interested in watching."

When organic and sponsored content align, endorsements appear intrinsically motivated, which buffers against the negative impacts of higher endorsement rates in relation to perceived manipulative intent. Conversely, sparse organic product mentions may exacerbate the cost of high endorsement rates, reinforcing suspicions that the influencer's motives are primarily commercial (Audrezet, De Kerviler, and Moulard 2020; Mardon, Cocker, and Daunt 2023). As a result, we predict a flattened cost curve of manipulative intent, such that the overall effect of endorsement rate on sponsored post engagement flattens out too. Formally:

> **H_3**: Organic product mentions weaken the U-shaped effect of endorsement rate on sponsored post engagement.

"Brand endorsement consistency" refers to the extent to which an influencer has repeatedly endorsed the same brand as the focal sponsored brand in their previous sponsored posts. While prior research suggests that consistent promotion of a particular brand can signal loyalty (Spiggle, Nguyen, and Caravella 2012), it may also weaken the signaling value of the influencer's endorsement rate in relation to their brand recognition, which in turn can diminish its impact on sponsored post engagement. An influencer–brand collaboration is a brand alliance between the influencer and the sponsoring brand (Leung et al. 2022). The literature on brand alliances suggests that such partnerships often serve as signals of quality to the market (Mishra et al. 2017; Rao and Ruekert 1994). For influencers, working with different brands can thus communicate their broad market appeal and commercial value. Similar to firms with extensive alliance networks, influencers who collaborate with multiple brands are perceived as having higher status and stronger validation from the market (Swaminathan and Moorman 2009).

In contrast, repeatedly endorsing the same brand may weaken the connection between endorsement rate and perceptions of the influencer's brand recognition. When consumers encounter a sponsored post from an influencer who has already promoted the same brand multiple times, they are less likely to interpret the endorsement rate as a sign of broad marketplace recognition. Instead, repeated endorsements are viewed more as reinforcement of an existing brand relationship. Such consistency may be viewed as redundant information that adds little to their evaluation of the influencer's quality and reputation (Mishra et al. 2017). Repeated collaborations may even be seen as a lack of diversity in opportunities. For example, one influencer who has consistently worked with a health supplement brand (Interviewee 1) remarked, "This strengthens my identity as a health-focused influencer while allowing me to provide them with consistent endorsements. But I sometimes wonder if it gives the impression that my market appeal is limited." Similarly, another influencer with a long-term partnership with Yamaha (Interviewee 5) noted, "While it is beneficial, it seems to limit my overall appeal to other brands. I still actively explore other brand partnerships, because working with different brands makes me look good and legitimate." These insights underscore that consumers may view influencers with consistent endorsements as less sought after by other brands, thereby diminishing the value of the influencer's endorsement rate as a signal of market recognition.

Taken together, repeated collaborations with a particular brand do not necessarily expand the influencer's perceived recognition across the brand marketplace. Instead, such consistency may indicate the influencer's dependence on a specific partner, thereby diminishing the extent to which a higher endorsement rate reflects broad market acknowledgment. Therefore, we predict that consistent brand endorsements weaken the benefit curve of perceived brand recognition, leading to a flatter overall effect of endorsement rate on sponsored post engagement.

> **H_4**: Brand endorsement consistency weakens the U-shaped effect of endorsement rate on sponsored post engagement.

Overview of Studies

To test the hypotheses, we conducted four studies, including both field studies and controlled experiments (see Table 2). In Study 1, we analyzed Instagram data from nearly 5,000 influencers to assess the main effect of endorsement rate on sponsored post engagement (H_1). In Study 2, we reaffirmed the observed U-shaped relationship and tested the proposed mediating mechanisms (H_2) through a controlled experiment. The experiment in Study 3 established the causal effect of endorsement rate on *actual* engagement behavior. Finally, in Study 4, we analyzed nearly five years of post-level data from 1,000 influencers on Douyin to provide a comprehensive test of our framework (H_1–H_4).

Study 1: Endorsement Rate on Instagram

Data

Study 1 aims to explore how influencers' historical endorsement rates affect consumer engagement with their subsequent sponsored posts (H_1). We gathered data from an Instagram analytics platform (hereafter, "data provider") that connects brands with influencers in Australia. The data provider tracks influencer posts and their engagement data daily. It also identifies sponsored posts in accordance with the Australian Influencer Marketing Council guidelines, which mandate the use of designated hashtags or the Instagram "Paid Partnership" tag to ensure influencers disclose advertisements in compliance with the Australian Consumer Law.[1]

From the data provider's pool of Australian influencers across 14 domains, we randomly sampled 5,000 influencers who had posted at least one sponsored post in October 2022. We collected each influencer's profile information, along with all their sponsored posts from that month, to form our main sample. For each focal sponsored post, we gathered its posting time, post attributes (e.g., post type, caption information), sponsorship disclosure method, and engagement metrics. Additionally, we collected the influencers' posting history over the 12 months preceding the focal post period (i.e., October 2021 to September 2022). This included each post's posting time, engagement metrics, and whether the post was sponsored. These data enabled us to compute endorsement rates and control variables related to the characteristics of prior posts. After excluding 92 influencers who registered their accounts after October 2021, the final sample consisted of 6,869 sponsored posts by 4,908 influencers in October 2022. We provide a breakdown of influencers by domain in Web Appendix C.

Measures and Models

Table 3 lists the variables, their operationalizations, and descriptive statistics. Following Wies, Bleier, and Edeling (2023), we measure the dependent variable—sponsored post engagement—with the number of comments and likes received by the focal sponsored post. We calculate the endorsement rate (ER) as the proportion of sponsored posts to total posts by the influencer prior to the focal sponsored post.

We also incorporate control variables to account for the effects of sponsored post characteristics, previous postings by the influencer, and attributes of the influencers themselves (Leung et al. 2022). For each sponsored post, we control for the type of post (Carousel or Video), the word count in the caption (Caption_length), and the number of hashtags (#Hashtags) and tagged users (#Tagged_users) in the caption. We also consider whether the sponsorship was disclosed using Instagram's partnership tag or advertising hashtags (Partnership_tag).

Consistent with Wies, Bleier, and Edeling (2023), we consider an influencer's posting history, because past activities may shape follower expectations and engagement with sponsored content. We include prior engagement (Prior_engagement), calculated as the average number of comments and likes on an influencer's

[1] The Australian Influencer Marketing Council specifies a set of required hashtags for sponsorship disclosures, including #Ad, #Advert, #Advertising, #Advertisement, #Sponsored, #PaidPartnership, and #PaidPromotion.

Table 2. Overview of Empirical Studies.

Study	Main Objective(s)	Data and Method	Platform	Key Findings
Study 1	To examine the effect of an influencer's endorsement rate on consumer engagement with sponsored posts (H_1)	Field data analysis of 6,869 sponsored posts from 4,908 influencers over one month	Instagram	Provides initial evidence that an influencer's endorsement rate has a U-shaped effect on sponsored post engagement
Study 2	To test the causal effect of endorsement rate on engagement intentions (H_1) and assess the mediating mechanisms (H_2)	Controlled experiment with engagement intention measures	Twitter (experimental setting)	Confirms the U-shaped effect of endorsement rate on engagement intentions and the mediating roles of perceived brand recognition and perceived manipulative intent
Study 3	To establish the causal effect of endorsement rate on actual engagement behavior (H_1)	Controlled experiment with a choice-compatible measure of actual engagement	Instagram (experimental setting)	Demonstrates causal evidence of the U-shaped effect of endorsement rate on actual engagement behavior
Study 4	To test the endorsement rate effect with panel data, assess moderation by organic product mentions (H_3) and brand endorsement consistency (H_4), and analyze the mediating mechanisms via consumer comments (H_2)	Field data analysis of 533,092 videos (including 147,877 sponsored videos) from 1,000 influencers	Douyin (Chinese TikTok)	Reconfirms the U-shaped effect of endorsement rate, which is weakened by organic product mentions and brand endorsement consistency; provides additional evidence of the mediating roles of perceived brand recognition and perceived manipulative intent

prior posts. We also include days elapsed since the influencer's last post (Days_last_post) to control for recency effects, days elapsed since the influencer's first post to control for their account age (Days_first_post), and post frequency (Post_frequency), which reflects the average time interval between posts (Leung et al. 2022).

Next, we control for the influencer's characteristics,[2] including the number of followers they had at the time the focal sponsored post was shared (Follower_count) and whether the influencer is a verified user on Instagram (Verified_profile). In addition, we include indicators of whether the influencer's self-identified account category (Show_category) (e.g., artist, blogger) and contact email (Show_email) are visible in their profile. Finally, to control for the potential effects of influencer domains (e.g., fashion, cooking), we include a vector of influencer domain dummies.

To examine the relationship between endorsement rate and sponsored post engagement (H_1), we apply a negative binomial regression, as is suitable for count data with overdispersion. The model specifications are as follows:

$$Y_{i,t} \sim \text{Negative Binomial}\ (\mu_{i,t},\ \alpha),$$

and

$$\text{Log}(\mu_{i,t}) = \beta_0 + \beta_1 ER_{i,t} + \beta_2 ER_{i,t}^2 + \delta X_{i,t} + \theta Z_i + v_t,$$

where $Y_{i,t}$ denotes the number of comments or likes for a sponsored post from influencer i posted at time t. It follows a negative binomial distribution, with mean $\mu_{i,t}$ and dispersion parameter α, such that we account for overdispersion. The vector $X_{i,t}$ contains the time-varying controls listed in Table 3, such as focal sponsored post characteristics, prior post characteristics, and follower count. The vector Z_i includes influencer-level controls that do not vary over time, such as the influencer domain or verification status. Finally, v_t represents date fixed effects. Correlations and variance inflation factors are presented in Web Appendix D.

Results

In Table 4, the linear terms of the endorsement rate have significant negative effects (comments: $\beta_{ER} = -1.812$, $p = .000$; likes: $\beta_{ER} = -1.152$, $p = .000$), and the quadratic terms of endorsement rate have significant positive effects (comments: $\beta_{ER}^2 = 1.908$, $p = .000$; likes: $\beta_{ER}^2 = 1.466$, $p = .000$) on the number of comments and likes of the sponsored post, in support of H_1.

Figure 1 depicts these U-shaped effects. Following Haans, Pieters, and He (2016), we formally assess the significance of this U-shaped relationship in two steps. First, we validate the slopes at the minimum and maximum observed endorsement rates in our dataset ($ER_{min} = .00$, $ER_{max} = .82$). The results in Table 5 reveal a significantly negative slope at the lower end ($\beta_{ER} + 2 \times \beta_{ER}^2 ER_{min}$) and a significantly positive slope at the higher end ($\beta_{ER} + 2 \times \beta_{ER}^2 ER_{max}$) for both comments and likes. Second, we calculate a turning point at $-\beta_{ER}/2\beta_{ER}^2$ and confirm its presence within the observed range. The bootstrap analyses (5,000 iterations) support the stability of turning points within the 95% confidence intervals (CIs) for both engagement metrics.

Further analyses reveal marginal effects of changes in endorsement rate on sponsored post engagement (see Web

[2] Because of the limited number of posts per influencer, we were unable to include influencer fixed effects in Study 1, as the model did not converge. This limitation is addressed in Study 4, where the longer panel makes fixed effects estimable.

Table 3. Variable Operationalizations (Study 1).

Variable	Operationalization	Mean	SD	Min	Max
Focal Sponsored Post Engagement					
Comments	Number of comments received by the focal sponsored post	96.87	857.71	0	32,294
Likes	Number of likes received by the focal sponsored post	632.23	2,419.90	0	62,001
Endorsement Rate					
ER	Proportion of sponsored posts to total posts by the influencer prior to the focal sponsored post	.16	.21	0	.82
Focal Sponsored Post Characteristics					
Carousel	Whether the post is a carousel post	.29	.46	0	1.00
Video	Whether the post is a video post	.29	.45	0	1.00
Caption_length	Word count of the post's caption	72.50	67.95	0	433
#Hashtags	Number of hashtags in the caption	6.25	8.28	0	34
#Tagged_users	Number of "@" mentions in the caption	1.73	2.98	0	20
Partnership_tag	Whether Instagram's "Paid Partnership" tag is used	.16	.37	0	1
Prior Post Characteristics					
Prior_engagement	Average number of comments and likes received by the influencer's posts over the past year	842.03	2,978.24	1	90,923.08
Days_last_post	Days elapsed since the influencer's last post	3.39	6.49	0	86.08
Days_first_post	Days elapsed since the influencer's first post	1,033.24	841.25	0	3,809.86
Post_frequency	Average time interval (in days) between posts	3.95	6.35	0	96.03
Influencer Characteristics					
Follower_count	Number of followers at the time the focal sponsored post was shared	83,782.6	185,989.4	630	6,188,742
Verified_profile	Whether the influencer is a verified user on Instagram	.28	.45	0	1
Show_category	Whether the influencer's account category is disclosed	.64	.48	0	1
Show_email	Whether the influencer's contact email is disclosed	.45	.50	0	1

Table 4. Impact of Endorsement Rate on Sponsored Post Engagement (Study 1).

Predictors	Model 1: Comments	Model 2: Likes
ER	−1.812 (.374) [.000]	−1.152 (.277) [.000]
ER^2	1.908 (.489) [.000]	1.466 (.362) [.000]
Carousel	−.037 (.052) [.472]	.051 (.039) [.186]
Video	−.053 (.052) [.306]	.220 (.039) [.000]
Caption_length	1.286 (.021) [.000]	.297 (.016) [.000]
#Hashtags	−.348 (.022) [.000]	−.176 (.017) [.000]
#Tagged_users	.012 (.021) [.569]	.072 (.016) [.000]
Partnership_tag	−.091 (.061) [.137]	−.132 (.045) [.004]
Prior_engagement	.229 (.025) [.000]	1.134 (.019) [.000]
Days_last_post	.096 (.023) [.000]	.010 (.017) [.562]
Days_first_post	.285 (.023) [.001]	.345 (.017) [.000]
Post_frequency	−.025 (.024) [.284]	−.049 (.018) [.006]
Follower_count	.447 (.026) [.000]	.383 (.019) [.000]
Verified_profile	.060 (.052) [.251]	.175 (.039) [.000]
Show_category	−.079 (.045) [.080]	.001 (.033) [.966]
Show_email	−.094 (.045) [.035]	−.093 (.033) [.005]
Influencer domain fixed effects	Included	Included
Day fixed effects	Included	Included
Observations	6,869	6,869
Wald χ^2	33,667.0	146,475.1
AIC	55,838	91,051

Notes: Robust standard errors are reported in parentheses, and *p*-values are in square brackets. AIC = Akaike information criterion. All variables, except ER, have been z-scored (standardized) for ease of interpretation and comparison.

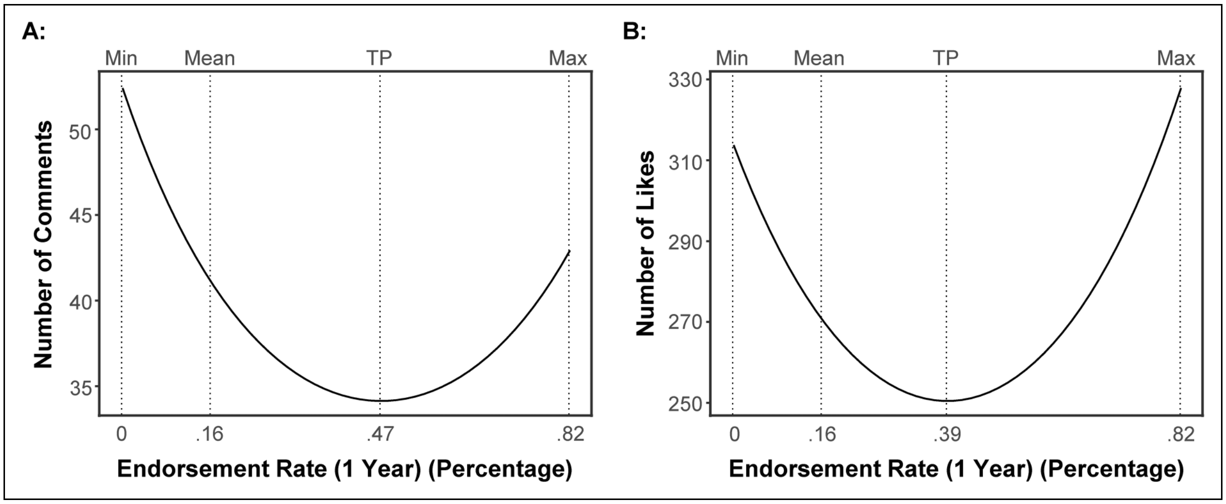

Figure 1. Plots of U-Shaped Effects (Study 1).
Notes: TP = turning point.

Table 5. Test of U-Shaped Effects (Study 1).

	Lower End: $\beta_{ER} + 2 \times \beta^2_{ER} ER_{min}$		Higher End: $\beta_{ER} + 2 \times \beta^2_{ER} ER_{max}$		Turning Point	
Dependent Variable	**Slope**	**t-Test**	**Slope**	**t-Test**	**ER**	**Confidence Interval**
Comments	−1.808	$t = -4.85$, $p = .000$	1.322	$t = 2.87$, $p = .004$	.475	[.414, .550]
Likes	−1.149	$t = -4.153$, $p = .000$	1.257	$t = 3.674$, $p = .000$	.393	[.312, .553]

Appendix E, Figure E1). We calculate marginal effects using the formula $e^{(\beta_{ER}+2\beta_{ER^2}\cdot ER)\Delta ER} - 1$, assuming a locally linear relationship between endorsement rate and engagement over a small range of ΔER. For comments, on the descending (left-hand) side of the U-shaped curve (Figure 1, Panel A), influencers with an average endorsement rate experience a 6.9% decrease in comment volume when their endorsement rate increases by 5%. On the ascending (right-hand) side, though, influencers with an observed average endorsement rate see a 4.3% rise in comment volume when the endorsement rate increases by 5%. For likes, the pattern is similar. On the left-hand side of the curve (Figure 1, Panel B), a 5% increase in endorsement rate leads to a 4.3% decrease in likes for influencers with an observed average endorsement rate, but on the right-hand side, influencers with an average endorsement rate experience a 3.6% increase in likes in response to a 5% increase in endorsement rate.

Robustness Checks

To confirm the reliability of our findings, we conducted several robustness checks, as detailed in Web Appendices E and F. First, we recalibrated our model using ordinary least squares (OLS) and Poisson regressions; they confirm the robustness of our findings. Second, we measured endorsement rate using alternative time windows (one, three, and six months prior to the focal sponsored post), since some followers (especially new ones) might rely more on recent posts when forming impressions. Third, because detailed endorsement information (e.g., brand or product characteristics) was unavailable, omitted variables may raise endogeneity concerns. To address this, we adopted a Gaussian copula method[3] (Park and Gupta 2012), which corrects for endogeneity without requiring instrumental variables or normality assumptions for potential endogenous regressors (Eckert and Hohberger 2023; Rutz and Watson 2019). The results again confirmed the U-shaped relationship (see Web Appendix F, Table F1). Finally, we examined possible simultaneity bias —that is, whether endorsement rates are shaped by prior engagement performance. Correlations between endorsement rates and past engagement were weak, suggesting such reverse causality is unlikely (see Web Appendix F, Figures F1 and F2).

Discussion

Study 1 offers initial evidence of a U-shaped impact of an influencer's endorsement rate on sponsored post engagement.[4] Despite efforts to mitigate bias, Study 1 has several limitations. First, it relies on a limited number of sponsored posts per

[3] We thank an anonymous reviewer for suggesting this method as a way to address endogeneity concerns.
[4] We conducted an additional study among U.S. Instagram influencers and obtained consistent results (Web Appendix G).

influencer and lacks information on the specific brands or products they endorsed. These constraints introduce the potential for confounds, particularly at the influencer and brand levels. Second, we lack access to the content of historical posts, which prevents us from controlling for differences across prior organic and sponsored posts. Our subsequent studies are designed to address these limitations. To start, Study 2 employs a controlled experimental design to rule out confounds and establish causality.

Study 2: Exploring the Mechanisms of Endorsement Rate in a Controlled Experiment

In a controlled experiment, we manipulate an influencer's endorsement rate, examine the roles of perceived brand recognition and perceived manipulative intent as underlying mechanisms, and test possible alternative explanations for the proposed U-shaped effect on sponsored post engagement.

Methods

We recruited 180 participants from Amazon Mechanical Turk in exchange for monetary compensation. After excluding 12 participants who failed the attention check question, the final sample size was 168 (43.45% female, 56.55% male; M_{age} = 35.51 years). All participants were required to have a personal Twitter (now known as X) account and to follow influencers on the platform.

Participants were instructed to imagine that they followed a cooking influencer on Twitter, a context chosen for its broad appeal on social media. They were randomly assigned to one of three endorsement rate conditions: low, medium, or high. They viewed five text-only Twitter posts from this influencer (for the stimuli, see Web Appendix H). In the low endorsement rate condition, all five posts were organic without sponsorship. In the high endorsement rate condition, four of the five posts were sponsored, clearly denoted by brand mentions ("@brand") and sponsorship hashtags (i.e., "#ad"). In the medium condition, two posts were sponsored, and three were organic. The random sequence of the five posts minimizes order effects, and each post was consistent in length.

After viewing the posts, participants saw the focal sponsored post, in which the influencer promoted a milk product. They rated their likelihood of engaging with this post on their personal Twitter accounts using three items ("like," "comment on," and "share"; 1 = "very unlikely," and 7 = "very likely"; Hughes, Swaminathan, and Brooks 2019; α = .87). They indicated their perceptions of the influencer's brand recognition with four items (e.g., "The influencer has been recognized by brands within his/her domain"; 1 = "strongly disagree," and 7 = "strongly agree"; Rapp et al. 2015; Winterich, Mittal, and Aquino 2013; α = .91) and their perceptions of manipulative intent with three items (e.g., "The influencer tried to manipulate the audience to buy the products in his/her posts"; 1 = "strongly disagree," and 7 = "strongly agree"; Campbell 1995; α = .72). We also administered a series of control measures to capture participants' familiarity with the promoted brand, engagement habits on Twitter, liking for cooking, and attention and mood levels during the experiment. These control variables did not differ across conditions ($p > .10$). The measurement items are detailed in Web Appendix I.

Results

Manipulation check. Participants rated the influencer's endorsement rate with three items on a seven-point Likert scale (1 = "not frequently at all," and 7 = "very frequently"; 1 = "never," and 7 = "always"; 1 = "at no time," and 7 = "every time"; α = .93). A one-way analysis of variance (ANOVA) revealed significant differences in perceived endorsement rate across conditions ($M_{low} = 4.04$, $M_{medium} = 5.05$, $M_{high} = 5.72$; $F = 25.568$, $p = .000$), confirming the success of our manipulation.

Sponsored post engagement. A one-way ANOVA showed a significant U-shaped effect of endorsement rate on sponsored post engagement, with a medium effect size ($F(1, 165) = 10.35$, $p = .002$, $\eta_p^2 = .06$), supporting H_1 (Figure 2, Panel A). Planned contrasts revealed that participants were more likely to engage with the sponsored post when the influencer had a low endorsement rate ($M = 4.90$, $SD = 1.23$) compared with a medium endorsement rate ($M = 4.22$, $SD = 1.74$; $t = 2.40$, $p = .017$, $d = .46$), reflecting a medium effect size. Engagement likelihood was also higher under a high endorsement rate ($M = 5.14$, $SD = 1.48$) than under a medium rate ($t = 3.23$, $p = .001$, $d = .62$), reflecting a medium-to-large effect size. No significant difference in engagement likelihood emerged between low and high endorsement rate conditions ($t = .85$, $p = .398$, $d = .16$).[5]

Perceived brand recognition and manipulative intent. Another one-way ANOVA indicated that endorsement rate had a significant impact on perceived brand recognition ($F(2, 165) = 9.19$, $p = .000$, $\eta_p^2 = .10$), reflecting a medium-to-high effect size. In the planned contrasts, we found no significant increase in perceived brand recognition when the endorsement rate increased from low to medium ($M_{low} = 4.81$, $SD = 1.56$; $M_{medium} = 4.99$, $SD = 1.14$; $t = .72$, $p = .472$, $d = .14$), but we observed a significant rise in perceived brand recognition when the endorsement rate escalated to high levels ($M_{high} = 5.74$, $SD = .91$; $t = 3.19$, $p = .002$, $d = .61$), indicating a medium-to-high effect.

Endorsement rate also significantly affects perceived manipulative intent, with a large effect size ($F(2, 165) = 16.74$, $p = .000$, $\eta_p^2 = .17$). Planned contrasts showed a medium-to-large increase in perceived manipulative intent from low to medium endorsement rates ($M_{low} = 4.62$, $SD = 1.30$; $M_{medium} = 5.29$, $SD = .65$; $t = 3.48$, $p = .000$, $d = .67$), followed by a smaller

[5] We conducted several robustness checks by examining liking, commenting, and sharing intentions as separate dependent variables. All results, as detailed in Web Appendix J, consistently support the U-shaped effect.

but significant increase (small-to-medium effect size) from medium to high endorsement rates ($M_{high} = 5.69$, $SD = .93$; $t = 2.05$, $p = .042$, $d = .39$). As shown in Figure 2, Panel B, the increase is more pronounced from low to medium than from medium to high rates ($MD_{medium\ vs.\ low} = .67$, $p = .000$; $MD_{high\ vs.\ medium} = .39$, $p = .042$).

Mediation analysis. For the multicategorical mediation analysis, we used Model 4 in the PROCESS macro (Hayes 2013), with 10,000 bootstrap samples. Similar to Yan, Keh, and Chen (2021), we introduced two dummy variables for the three endorsement rate conditions (X1: low = 1, medium = 0, high = 0; X2: low = 0, medium = 0, high = 1), with medium endorsement rate as the reference group. The results confirmed that perceived brand recognition exerted significant mediation only between the medium and high endorsement rate conditions ($\beta_{X2} = .37$, $SE = .15$, 95% CI = [.111, .707]), not between the low and medium conditions ($\beta_{X1} = -.08$, $SE = .13$, 95% CI = [−.337, .193]). The beneficial impact of endorsement rate on engagement, in terms of perceived brand recognition, became more profound as the endorsement rate increased from medium to high levels. In contrast, perceived manipulative intent significantly mediated the variations in sponsored post engagement between both low and medium ($\beta_{X1} = .24$, $SE = .14$, 95% CI = [.017, .548]) and medium and high ($\beta_{X2} = -.14$, $SE = .09$, 95% CI = [−.345, −.003]) endorsement rate conditions. These findings collectively support H_2.

Alternative explanations. We further explored other potential mediators. Influencers who frequently endorse products might appear more informative (Lou and Yuan 2019), so we assessed their perceived informativeness using items adapted from Woltman Elpers, Wedel, and Pieters (2003). Influencers with high endorsement rates also might seem more socially distant (Mardon, Cocker, and Daunt 2023), and we accordingly measured social connectedness with two items adapted from Jiang et al. (2010). As Web Appendix K shows, neither variable exerted significant mediation effects.

Simulation analyses. Following Wies, Bleier, and Edeling (2023), we conducted simulation analyses to examine the ranges of perceived brand recognition and manipulative intent within which the U-shaped relationship between endorsement rate and sponsored post engagement holds. We aligned the attitudinal measure of engagement likelihood from Study 2 with predicted engagement by calculating the corresponding engagement rate. We then modeled the relationships among endorsement rate, the mediators, and predicted engagement. For each endorsement rate condition (low vs. medium vs. high), we identified combinations of mediator values that would produce a U-shaped relationship between endorsement rate and predicted engagement. As detailed in Web Appendix L, the observed values of the mediators from Study 2 fall well within the ranges in which the U-shaped relationship is expected to manifest.

Discussion

Study 2 replicates the U-shaped effect of endorsement rate on sponsored post engagement in a controlled setting and confirms the mediating roles of perceived brand recognition and perceived manipulative intent as core mechanisms driving this effect. The observed effect sizes are largely in the medium-to-large range, highlighting the robustness of the findings. In the next study, we aim to capture actual post engagement behavior in another experimental setting, to enhance the generalizability of our results and strengthen the validity of our causal inferences.

Study 3: Endorsement Rate and Actual Post Engagement

In Study 3, we conduct another controlled experiment using a choice-compatible design to capture actual engagement behavior, namely, whether participants actually shared a sponsored post through their personal accounts.[6] To enhance generalizability, the study uses Instagram as the research context, and we rule out additional alternative explanations for the U-shaped effect.

Method

We recruited 215 students from a large university in Hong Kong in exchange for course credit. After excluding 7 participants who failed the attention check, the final sample size was 208 (67.31% female, 32.69% male; $M_{age} = 20.35$ years). All participants had a personal Instagram account and followed influencers on the platform.

As a cover story, participants read that the research team was collaborating with influencers to gather participants' perceptions. They viewed five posts from a fashion influencer on an Instagram account created specifically for this study. Similar to Study 2, none, two, and four of the five posts were sponsored in the low, medium, and high endorsement rate conditions, respectively (Web Appendix M). The sponsored posts included brand mentions ("@brand"), sponsorship hashtags (i.e., "#sponsored," "#[brand name]"), and Instagram's official paid partnership label, in line with common practices for disclosing sponsorships (Meta 2024). Each post included four lines of caption text and a picture, which was the same across conditions.

After viewing the posts, participants encountered the focal sponsored post, in which the influencer promoted a duffel bag. To capture actual post engagement behaviors, we used a choice-compatible design (Costello, Walker, and Reczek 2023; Goor, Keinan, and Ordabayeva 2021). Participants were informed that they could enter a lottery to win the promoted duffle bag from the influencer if they shared the post on their Instagram stories using their own account. Those who opted to share actually had to share the post on their own Instagram story and verify that action with the lab manager. We measured

[6] The experiment was preregistered at https://aspredicted.org/FXZ_CYD.

the control variables from Study 2 and found no significant differences across conditions.

Results

Participants indicated the influencer's endorsement rate, as in Study 2. A one-way ANOVA showed significant differences across conditions ($M_{low} = 4.26$; $M_{medium} = 5.07$; $M_{high} = 5.60$; $F = 17.497$, $p = .000$), confirming the success of our manipulation. To test for the impact of endorsement rate on participants' actual post engagement behavior, we conducted a chi-square test. As anticipated, a greater proportion of participants in both the high ($N = 32$, 44.44%) and low ($N = 28$, 41.79%) endorsement rate conditions shared the focal sponsored post on their personal Instagram account, compared with the medium endorsement rate condition ($N = 15$, 21.74%; $\chi^2(2) = 9.29$, $p = .010$; Cramer's $v = .21$), reflecting a low-to-medium effect size. Further ANOVA and planned contrast tests revealed a significant U-shaped effect of endorsement rate ($F(1, 205) = 9.43$, $p = .002$, $\eta_p^2 = .05$; $MD_{low\ vs.\ medium} = .20$, $t = 2.47$, $p = .014$, $d = .42$; $MD_{high\ vs.\ medium} = .23$, $t = 2.85$, $p = .005$, $d = .48$), with all effect sizes in the medium range. Yet we observed no significant differences in actual post engagement behaviors between the low and high endorsement rate conditions ($t = .33$, $p = .741$, $d = .06$).

Beyond the alternative explanations tested in Study 2, we acknowledge that varying endorsement rates might influence perceptions of an influencer's expertise (Schouten, Janssen, and Verspaget 2021), trustworthiness (Leung, Gu, and Palmatier 2022), opinion leadership (Lin, Bruning, and Swarna 2018), and transparency (Cao and Belo 2023). A series of ANOVAs and mediation analyses show that none of these variables significantly mediate the focal relationship, so we can rule them out as alternative explanations (see Web Appendix K).

Discussion

Study 3 substantiates the U-shaped impact of influencers' endorsement rate on sponsored post engagement using a choice-compatible design. This approach not only supplements the findings in Study 1 with causal evidence but also builds on the findings from Study 2 by capturing participants' actual engagement behaviors. The observed medium effect sizes further underscore the robustness of the findings. In the next study, we gather a more comprehensive dataset to validate our conceptual framework and, in particular, to test the proposed moderators.

Study 4: Boundary Conditions for the Effect of Endorsement Rate

In Study 4, we seek more granular insights into our research model by analyzing video-level data from Douyin. With this data, we can investigate the predicted moderating roles of organic product mentions and brand endorsement consistency (H_3 and H_4). We also leverage textual data obtained from consumer comments on the influencers' posts to reexamine the mediating roles of perceived brand recognition (H_{2a}) and manipulative intent (H_{2b}).

Data

We partnered with a leading media data provider to gather data from Douyin, the Chinese version of TikTok. With 795.3 million users (Statista 2024), Douyin represents one of the most popular short-video platforms in China. The data provider monitors more than 1 million Douyin influencers daily and collects their new posts. We focused on five domains with the largest influencer populations: fashion, food, entertainment, home, and health and fitness. For each domain, we randomly selected 200 influencers with varying follower counts, for a total of 1,000 sampled influencers; we excluded official brand and celebrity accounts. A summary of the sampled influencers' demographics is available in Web Appendix N, Table N1.

The dataset includes all videos posted by the sampled influencers since the inception of their Douyin accounts. For each video post, we extracted the video content, posting time, caption, and engagement metrics (i.e., reposts, comments, likes). For the sponsored videos specifically, we also collected information about endorsed products and brands. Douyin began supporting sponsored content in January 2018. A distinctive feature of Douyin's product sponsorship function is that it allows influencers to embed purchase links in their posts, providing a seamless, in-app pathway to buy the endorsed products (see Web Appendix N, Figure N1). Using these embedded links, we identified 147,877 sponsored videos, which collectively promote 60,332 unique products from 10,762 brands across 61 product categories. In addition to this main sample, we also leveraged the full set of video posts, including all organic posts each influencer made, to construct key variables. These include endorsement rate, organic product mentions, and controls related to influencers' prior posting behavior.

Measures

Table 6 details the operationalizations of the key variables and their descriptive statistics.

Sponsored post engagement. The dependent variable, sponsored post engagement, reflects the number of reposts each focal sponsored video received. We selected reposts as an engagement measure for this study because reposting represents a deeper form of engagement than liking or commenting (Leung et al. 2022). In robustness checks, we also analyzed the number of likes and comments.

Endorsement rate. As in Study 1, we calculated the endorsement rate (ER) as the proportion of an influencer's sponsored videos to total videos posted prior to the focal sponsored video. Overall, the data reveal considerable variation in key influencer characteristics across different ER levels (see Web Appendix N, Figures N2–N5).

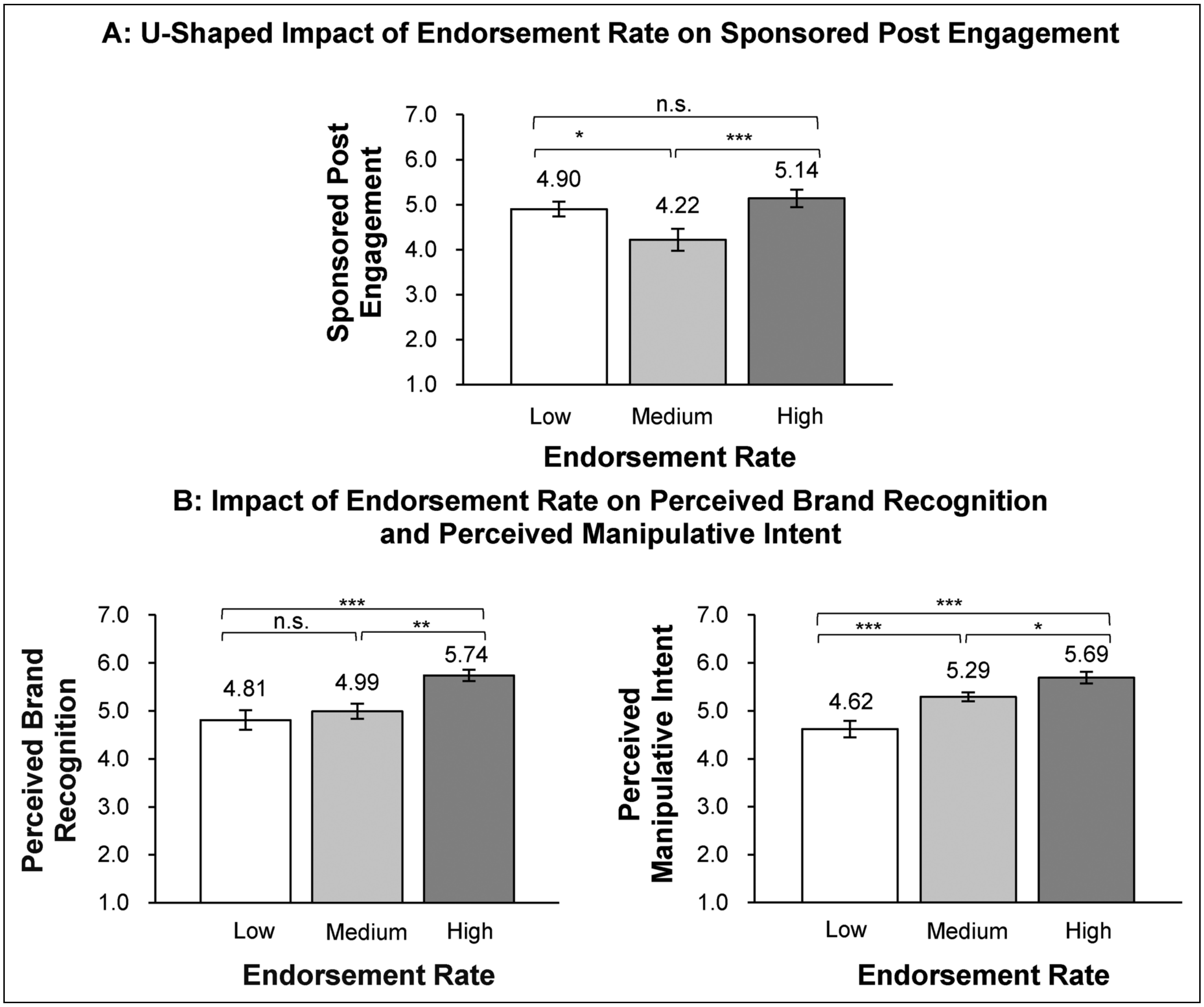

Figure 2. Underlying Mechanisms Across Endorsement Rate Conditions.
Notes: The error bars represent ±1 standard error. *$p < .05$, **$p < .01$, *** $p < .001$.

Moderators. To measure organic product mentions (Organic_mention), we used a multimodal deep learning method. Since the data provider does not supply product annotations for organic posts, we used the procedure in Web Appendix O. It entailed transcribing audio from influencers' organic videos using OpenAI's Whisper model and combining the transcripts with post captions. To identify product mentions, we developed a custom named-entity recognition model by fine-tuning a Chinese BERT model (Cui et al. 2021), which we then used to detect product type mentions in each video. We calculated Organic_mention as the proportion of organic videos mentioning the same product type as the focal sponsored video. Finally, as brand information is available for all sponsored posts, we gauged Brand_consistency as the number of times the endorsed brand appeared in the influencer's prior sponsored videos.

Control variables. Similar to Study 1, we accounted for potential effects of the sponsored post characteristics, the influencers' follower count at the time of posting (Follower_count), and previous activity patterns. For each sponsored post, we included general features such as the number of hashtags (#Hashtags), video length (Duration), and product description length (Description), as well as the number of products (#Products) and brands (#Brands) endorsed.

We also included variables that could not be measured in Study 1. To reflect the breadth of the influencer's endorsements, we included the number of unique brands (Brand_diversity) and product categories (Category_diversity) previously endorsed. To control for competition effects, we counted the number of brands in the same category that the influencer previously endorsed (#Competing_brands). We also gauged brand popularity by tracking the number of followers of the brand's official Taobao storefront (Brand_popularity). To account for brand variability in endorsements, we considered whether the currently endorsed brand differed from the last one endorsed (Brand_transition). Finally, we controlled for any remaining unobserved heterogeneity by including fixed effects for time, influencer, and product category.

Similar to Study 1, we used negative binomial regression to estimate the repost counts, which are prone to overdispersion. The engagement model, including moderating effects, is

$$\text{Repost}_{i,t} \sim \text{Negative Binomial}\ (\mu_{i,t},\ \alpha),$$

and

$$\begin{aligned}\text{Log}(\mu_{i,t}) = {} & \beta_0 + \beta_1 \text{ER}_{i,t} + \beta_2 \text{ER}^2_{i,t} + \beta_3 \text{ER}_{i,t} \times \text{Organic\_mention}_{i,t} \\ & + \beta_4 \text{ER}^2_{i,t} \times \text{Organic\_mention}_{i,t} \\ & + \beta_5 \text{ER}_{i,t} \times \text{Brand\_consistency}_{i,t} \\ & + \beta_6 \text{ER}^2_{i,t} \times \text{Brand\_consistency}_{i,t} \\ & + \beta_7 \text{Organic\_mention}_{i,t} + \beta_8 \text{Brand\_consistency}_{i,t} + \delta X_{i,t} \\ & + \Upsilon \text{IMR}_{i,t} + z_i + v_t,\end{aligned}$$

where the vector $X_{i,t}$ contains the time-varying controls listed in Table 6, z_i denotes the influencer fixed effects, and v_t represents date fixed effects.

Identification Strategy

To address the potential for brand selection bias—where brands might select influencers strategically based on their endorsement patterns (Cheng and Zhang 2024)—we applied a two-stage Heckman correction. In the selection stage, we estimated the likelihood of influencer i being sponsored by brand j using a probit model. In line with prior research (Wies, Bleier, and Edeling 2023), we included controls for influencer attributes (e.g., gender, age, follower demographics, endorsement rates, post frequency, and prior engagement), while also including fixed effects for influencers' domains, interest tags, and regions to capture unobservable heterogeneity. Similar to Leung et al. (2022), and Wies, Bleier, and Edeling (2023), we used the brand's collaboration with the influencer most similar to the focal influencer as an exclusion restriction. The rationale is that brands are likely to select both influencers with similar characteristics, yet the activities of the "most similar" influencer should not directly affect the focal influencer's engagement outcomes. We measured similarity based on the frequency with which pairs of influencers endorsed the same brands and identified the influencer with the greatest endorsement overlap as the "most similar." The selection model thus includes an indicator that equals 1 if the "most similar" influencer also endorses the focal brand, and 0 otherwise. As the results in Web Appendix P show, the exclusion restriction exerts a significant impact on the selection outcome, which validates our identification strategy. We incorporate the inverse Mills ratio (IMR), derived from the selection model, into the main analysis as a control.[7]

[7] As Heckman's correction assumes a continuous outcome, we computed the IMR using OLS. Although our models are count-based, the coefficients of IMR in OLS and count models are similar, suggesting that any misspecification bias is negligible.

Results

We analyzed the 147,877 sponsored posts using negative binomial regression models. The results for the main effects, curvilinear effects, and moderation models are in Table 7. Figure 3 illustrates the U-shaped relationship between endorsement rate and reposts (Panel A), with Panels B and C showing the moderating effects of organic product mentions and brand endorsement consistency. These plots are based on the marginal estimates from the fitted models reported in Table 7. Specifically, the interaction plots for the two moderators depict curves at three levels of the moderating variable: at 0 (note that a value one standard deviation below the mean falls outside our data range), at the mean, and at one standard deviation above the mean.

Model 1 reveals a significant positive quadratic term and a significant negative linear term for endorsement rate ($\beta^2_{ER} = 1.868$, $p = .000$; $\beta_{ER} = -1.938$, $p = .000$), in support of the U-shaped effect we predicted in H_1. Also, in support of H_3, Model 2 depicts a negative and significant quadratic interaction term for organic product mentions ($\beta^2_{OM\times ER} = -.375$, $p = .000$). Panel B in Figure 3 demonstrates a clear weakening effect: More frequent organic mentions diminish the impact of endorsement rate on engagement. The negative and significant quadratic interaction term for brand endorsement consistency ($\beta^2_{BEC\times ER} = -.706$, $p = .000$) in Model 3 supports H_4: Greater consistency flattens the U-shaped relationship between endorsement rate and engagement. In Panel C of Figure 3, the curve for high brand endorsement consistency (solid line) appears significantly flatter than the curve for low brand endorsement consistency (dotted line). Model 4, which incorporates both moderators, consistently indicates a flattening effect of these factors on the U-shaped curve. Panels D and E of Figure 3 further illustrate that the marginal effect of endorsement rate on engagement diminishes as organic product mentions and brand endorsement consistency increase.

We assessed the significance of the main and moderated U-shaped relationships. In Model 1, we estimated the main U-shaped relationship and observed a significantly negative slope at the lower end of endorsement rate ($\beta_{ER} + 2 \times \beta^2_{ER} \text{ER}_{min} = -1.938$, $p = .000$) and a significantly positive slope at the upper bound ($\beta_{ER} + 2 \times \beta^2_{ER} \text{ER}_{max} = 1.799$, $p = .000$). The turning point, calculated as $-\beta_{ER}/2\beta^2_{ER}$, is .519, well within the observed range of endorsement rates (0 to 1). We also examined the impact of endorsement rate on the number of reposts across different levels of our moderators by assessing their slopes and turning points in Models 2 and 3. The results, detailed in Web Appendix Q, consistently show a significant U-shaped impact. Moreover, we explored whether the moderators induced shifts in the turning point. Following Haans, Pieters, and He (2016), we set values for organic product mentions and brand endorsement consistency at 0 and then at the 75% quantile value. We observed a slight shift in turning points, by .005 (from .525 to .520) for organic product mentions; delta methods confirmed that this shift was significant ($p = .000$). A similarly significant

Table 6. Variable Operationalizations and Descriptive Statistics (Study 4).

Variable	Operationalization	Mean	SD	Min	Max
Sponsored Post Engagement					
Reposts	Number of reposts from the focal sponsored video	185.4	2,468.6	0	189,261
Comments	Number of comments from the focal sponsored video	174.5	1,158.1	0	61,297
Likes	Number of likes from the focal sponsored video	5,002.4	37,888	0	2,190,051
Endorsement Rate					
ER	Proportion of sponsored posts to total posts by the influencer prior to the focal sponsored post	.61	.27	0	1
Moderators					
Organic_mention	Proportion of organic videos that mentioned a product of the same type as featured in the focal sponsored video	.05	.14	0	.98
Brand_consistency	Count of occurrences of the focal sponsored brand in the influencer's previous sponsored videos	19.78	47.94	0	746
Controls (Follower Count and Characteristics of Prior Posts)					
Follower_count	Follower count on the date of posting the sponsored post	1,385,938	3,539,930	939	40,712,643
Days_first_post	Days elapsed since the influencer's first post	488.7	231.7	0	1,698.7
Days_last_post	Days elapsed since the influencer's last post	2.13	28.72	0	316.67
Post_frequency	Average time interval (in days) between posts	1.95	3.00	.01	164.11
Prior_engagement	Average engagement, combining counts of reposts, comments, and likes, on the influencer's previous posts	11,636.9	37,988.4	10.07	1,246,327
Controls (Focal Sponsored Post Characteristics)					
#Hashtags	Number of hashtags included in the caption of the focal sponsored video	1.52	1.38	0	12
Duration	Duration of the focal sponsored video (in seconds)	22.83	82.21	2	1,265.5
Description	(Average) word count of the description(s) of the product(s) featured in the focal sponsored video	26.20	7.94	2	90
#Products	Number of products featured in the focal sponsored video	1.12	.51	1	7
#Brands	Number of brands featured in the focal sponsored video	1.02	.16	1	7
Controls (Characteristics of Previously Endorsed Products)					
Brand_diversity	Number of unique brands previously endorsed by the influencer	65.41	91.28	0	421
Category_diversity	Number of product categories previously endorsed by the influencer	2.87	4.00	0	17
#Competing_brands	Number of brands in the same product category previously endorsed by the influencer	27.86	45.66	0	435
Controls (Characteristics of Focal Endorsed Products)					
Brand_popularity	Number of followers of the brand's official Taobao storefront (0 for brands without official storefronts)	1,231,879	5,146,573	0	74,075,124
Brand_transition	Whether the endorsed brand differs from the last brand endorsed by the influencer	.84	.36	0	1

yet slight leftward shift in reposts occurred for brand endorsement consistency (from .532 to .520, $p = .000$).[8]

We examine the marginal effects of changes in endorsement rate on reposts and use these insights to predict the economic implications of such variations. On the left-hand side of the curve, influencers with an average endorsement rate experience a 4.4% drop in reposts when the endorsement rate increases by 5%. According to the data provider, each repost of a sponsored post containing product links on Douyin correlates with an average of 21.7 sales units, with a mean product price of 118 CNY (US$16.24). The predicted reduction translates into 172.7 fewer sales units, or approximately U.S. $2,804 in lost product sales. On the right-hand side of the curve, influencers with an average endorsement rate see a 4.9% increase in reposts when the endorsement rate rises by 5%, corresponding to 199.5 additional sales units, or about U.S. $3,239 in increased sales. The impacts of the endorsement rate on reposts vary between .8% and 4.9% as the moderator levels move from low to high (see Web Appendix R).

[8] Although we observed significant shifts in turning points, such shifts serve as the primary mode of moderation only when the moderator influences the underlying linear mechanism (Haans, Pieters, and He 2016). In our study, both perceived brand recognition and manipulative intent follow curvilinear patterns. Thus, the observed shifts are largely due to curve flattening and are not of central theoretical relevance.

Post Hoc Analyses

To examine the mediators further, we collected 2,015,022 comments from 24,199 sponsored videos posted by 250 influencers, whom we selected randomly from an initial sample of 1,000 influencers. In the absence of established algorithms for assessing our constructs of perceived brand recognition and perceived

Table 7. Impact of Endorsement Rate on Douyin Sponsored Post Engagement.

	Model 1	Model 2	Model 3	Model 4
Independent Variables				
ER	−1.938 (.181) [.000]	−1.919 (.181) [.000]	−1.776 (.183) [.000]	−1.754 (.183) [.000]
ER^2 (H_1)	1.868 (.159) [.000]	1.860 (.159) [.000]	1.752 (.161) [.000]	1.741 (.161) [.000]
Interaction Terms				
Organic_mention × ER		.493 (.104) [.000]		1.060 (.201) [.000]
Organic_mention × ER^2 (H_3)		−.375 (.092) [.000]		−.729 (.149) [.000]
Brand_consistency × ER			1.030 (.201) [.000]	.504 (.104) [.000]
Brand_consistency × ER^2 (H_4)			−.706 (.149) [.000]	−.380 (.092) [.000]
Moderators				
Organic_mention	.130 (.008) [.000]	−.001 (.027) [.961]	.130 (.008) [.000]	−.005 (.027) [.845]
Brand_consistency	.001 (.007) [.912]	.001 (.007) [.914]	−.352 (.066) [.000]	−.361 (.066) [.000]
Controls				
Follower_count	.126 (.007) [.000]	.126 (.007) [.000]	.127 (.007) [.000]	.127 (.007) [.000]
Days_first_post	−.130 (.012) [.000]	−.132 (.012) [.000]	−.127 (.012) [.000]	−.128 (.012) [.000]
Days_last_post	−.017 (.006) [.004]	−.014 (.006) [.015]	−.018 (.006) [.002]	−.015 (.006) [.008]
Post_frequency	.090 (.009) [.000]	.090 (.009) [.000]	.091 (.009) [.000]	.090 (.009) [.000]
Prior_engagement	.182 (.016) [.000]	.184 (.016) [.000]	.181 (.016) [.000]	.182 (.016) [.000]
#Hashtags	.017 (.005) [.002]	.016 (.005) [.003]	.016 (.005) [.002]	.016 (.005) [.003]
Duration	.973 (.022) [.000]	.971 (.022) [.000]	.972 (.022) [.000]	.970 (.022) [.000]
Description	.019 (.006) [.002]	.019 (.006) [.002]	.018 (.006) [.003]	.018 (.006) [.003]
#Products	.056 (.012) [.000]	.055 (.012) [.000]	.057 (.012) [.000]	.057 (.012) [.000]
#Brands	.150 (.035) [.000]	.150 (.035) [.000]	.149 (.035) [.000]	.149 (.035) [.000]
Brand_diversity	.234 (.019) [.000]	.237 (.019) [.000]	.227 (.019) [.000]	.229 (.019) [.000]
Category_diversity	−.056 (.011) [.000]	−.058 (.011) [.000]	−.053 (.011) [.000]	−.054 (.011) [.000]
#Competing_brands	−.052 (.006) [.000]	−.052 (.006) [.000]	−.053 (.006) [.000]	−.053 (.006) [.000]
Brand_popularity	.025 (.007) [.000]	.025 (.007) [.000]	.024 (.007) [.000]	.024 (.007) [.000]
Brand_transition	.086 (.015) [.000]	.085 (.015) [.000]	.080 (.015) [.000]	.079 (.015) [.000]
IMR	−.072 (.020) [.000]	−.074 (.020) [.000]	−.075 (.020) [.000]	−.077 (.020) [.000]
Other Fixed Effects				
Period of day	Included	Included	Included	Included
Year-month-day	Included	Included	Included	Included
Influencer	Included	Included	Included	Included
Product category	Included	Included	Included	Included
Observations	147,877	147,877	147,877	147,877
Wald test	79,889.1	79,608.2	79,918.0	79,941.0
AIC	1,127,954	1,127,934	1,127,931	1,127,908

Notes: Robust standard errors are reported in parentheses, and *p*-values are in square brackets. All variables, except ER, were mean-centered for ease of comparison.

manipulative intent, we trained a specialized classification model using OpenAI's GPT-4, in combination with a fine-tuned Chinese BERT model (Cui et al. 2021). Large language models like BERT have demonstrated strong performance in text classification tasks (Chakraborty, Kim, and Sudhir 2022; D'Assergio et al. 2024), and GPT-4 achieves accuracy levels comparable to those of human coders in text categorization tasks (Xu et al. 2024). We applied these tools to identify comments referring to the influencer's brand recognition or manipulative intent, then validated the accuracy of their assessments manually (for details, see Web Appendix S).

We first examined how consumer sentiments expressed in each sponsored post respond to the influencer's endorsement rate. As shown in Web Appendix T, Table T1, the number of comments acknowledging the influencer's brand recognition significantly increased with endorsement rate, at an accelerating rate ($\beta_{ER} = 3.645$, $p = .000$; $\beta^2_{ER} = 1.053$, $p = .000$). The number of comments questioning the influencers' manipulative intent instead significantly increased with endorsement rate, at a decreasing rate ($\beta_{ER} = .832$, $p = .000$; $\beta^2_{ER} = -1.364$, $p = .000$). The results of additional tests of the moderating roles of organic product mentions and brand endorsement consistency in shaping the curvilinear effects of endorsement rate on consumer perception (Web Appendix T, Table T1 and Figure T1) indicate that organic product mentions significantly moderated the concave relationship between endorsement rate and perceived manipulative intent by smoothing the curve ($\beta^2_{OM \times ER} = .791$, $p = .000$). Conversely, brand endorsement consistency significantly flattened the curve of perceived brand recognition ($\beta^2_{BEC \times ER} = -.620$, $p = .000$). Finally, when we use lagged comment sentiment from each sponsored post to predict

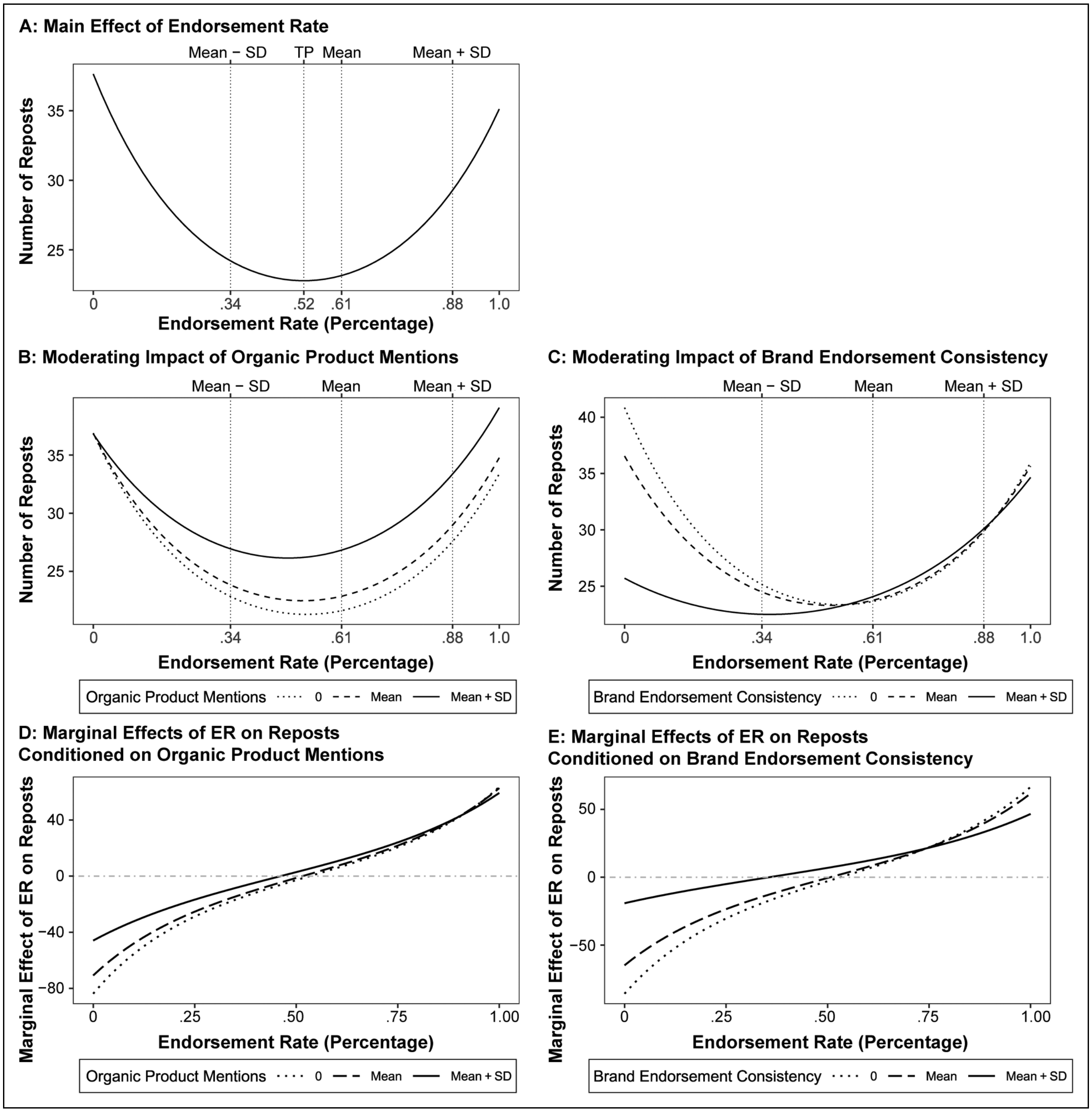

Figure 3. Plots of U-Shaped Effects and Moderating Effects for Reposts (Study 4).
Notes: TP = turning point.

reposts of the subsequent post, the results show that the proportion of comments praising the influencer's brand recognition significantly boosted reposts ($\beta_{BR} = .051$, $p = .011$), whereas the proportion of comments critical of the influencer's manipulative intent significantly reduced the number of reposts of the subsequent sponsored post ($\beta_{MI} = -.039$, $p = .033$).

Robustness Tests

To ensure the robustness of our findings, we reassessed the models using three alternative measures for endorsement rate: ER (interval), an inverse measure that captures the average time between consecutive sponsored videos, as well as ER (1 M) and ER (3 M), which gauge the proportion of sponsored videos during the 30 days (one month) and 90 days (three months) before the focal video, respectively, to capture recency effects. We also employed different engagement metrics (e.g., likes, comments) and model specifications (e.g., OLS, Poisson regressions), and we reevaluated the moderation models with alternative measures of the moderators. All the results offer consistent support for our findings (see Web Appendix U). Given the rich endorsement information available in Study 4, we addressed potential brand selection bias using Heckman's correction and assessed other identification concerns, such as consumer selection on endorsement rate (see Web Appendix V). Analyses of sample distributions further indicate that any remaining selection issues related to our moderators are minimal. Although omitted variables are less concerning in Study 4 due to the inclusion of influencer fixed effects, we applied the Gaussian copula method, as in Study 1, to account for potential unobserved endogeneity. Consistent with Study 1, we also examined the possibility of simultaneity by assessing whether endorsement rates are strategically adjusted in response to prior engagement performance. The descriptive patterns presented in Web Appendix V suggest this is unlikely to be a major concern.

General Discussion

Across four studies, we uncover the complex effects of influencers' endorsement rates on consumer engagement with sponsored posts. By examining the psychological mechanisms underlying these effects and outlining content strategies that can shift them, we illuminate the diverse impacts and boundary conditions of endorsement rate. Accordingly, this work offers fresh insights into influencer endorsement tactics.

Theoretical Contributions

The main contribution of this research to the influencer marketing literature lies in its in-depth examination of a crucial yet often overlooked characteristic: endorsement rate. While extensive research has explored various influencer attributes and their implications for marketing effectiveness (e.g., Beichert et al. 2024; Gu, Zhang, and Kannan 2024; Leung et al. 2022), the specific role of endorsement rate remains underexplored. By conceptualizing endorsement rate as the proportion of brand-sponsored posts to total social media posts, our study extends prior research that considers sponsored content in isolation, such as works on the number of prior sponsorships (Beichert et al. 2024) or on sponsorship disclosure (Cao and Belo 2023).

Substantiated by both field and experimental studies, our findings elucidate the critical role of endorsement rate in influencer marketing. We reveal a U-shaped effect on consumer engagement, challenging the traditional view that more endorsements lead to consumer backlash (Beichert et al. 2024; Garnès 2019). Rather, consumers' perceptions of sponsored posts may be better understood in relation to the total number of posts on the influencer's profile, where both high and low endorsement rates can enhance evaluations of future sponsored content. Recognizing this U-shaped relationship also broadens insights into the tension between authenticity and commercialization in influencer marketing (Audrezet, De Kerviler, and Moulard 2020; Chung, Ding, and Kalra 2023).

Celebrity endorsement literature has highlighted the adverse impacts of increased celebrity endorsements, primarily due to diminished perceptions of credibility (Mowen and Brown 1981; Tripp, Jensen, and Carlson 1994). Our findings reveal a similar trend among influencers: An escalating endorsement rate increases perceptions of manipulative intent that can undermine consumer engagement. However, unlike traditional celebrities, influencers can counterbalance the negative perceptions of manipulative intent with enhanced perceptions of brand recognition, which validates influencers' ability and value. This key difference distinguishes celebrities, whose reputations are grounded in professional achievements, from influencers, who can establish recognition through brand engagement and sponsorships.

This research also extends prior considerations of curvilinear effects of influencer characteristics on consumer engagement, such as emotional expressions (Bharadwaj et al. 2022) and follower count (Wies, Bleier, and Edeling 2023). As we demonstrate, the complex impact of influencer characteristics on consumer behavior is rooted in the multifaceted nature of consumer evaluations. Perceived brand recognition and manipulative intent serve as dual, countervailing mediators of the endorsement rate's effect on engagement. The U-shaped relationship arises because changes in endorsement rate shift the dynamics between positive perceptions of brand recognition and negative perceptions of manipulative intent.

Building on these dual mechanisms, we identify two content elements—organic product mentions and brand endorsement consistency—that mitigate the U-shaped influence of endorsement rate. In line with Morhart et al. (2015), who emphasize the importance of conveying intrinsic motives, our findings suggest that aligning sponsored content with influencers' genuine interests, as exhibited in their organic content, can alleviate consumer skepticism about manipulative intent related to endorsement rate. Moreover, a strategy that involves consistent brand endorsements can signal the influencer's genuine appreciation for a brand, though it may also signal a narrow brand scope, which could reduce perceived brand recognition. These insights resonate with Chen, Yan, and Smith's (2023) observation that authenticity and commercialization in influencer marketing can coexist through thoughtful content strategies. Our research contributes by delineating how contextual factors from influencers' past content shape consumer perceptions of their future endorsement practices.

Managerial Implications

The U-shaped relationship between an influencer's endorsement rate and consumer engagement challenges the conventional wisdom (Garnès 2019; Ritschel 2018) and suggests a more nuanced reality. Our findings indicate that influencers at both ends of the spectrum—those with low endorsements rates and those who frequently collaborate with brands—can generate strong consumer engagement with their sponsored content. This pattern suggests that distinct positioning choices exist at both ends of the spectrum, each offering unique value propositions to different audience segments (Leung, Gu, and Palmatier 2022) and echoing the classic segmentation–targeting–positioning framework in marketing. In our interviews, we learned that many influencers intentionally define their positioning early in their entrepreneurial journey. Some are primarily motivated by a desire to share personal interests and values (e.g., Interviewees 2, 7, and 8), while others purposefully build their influence to enable future monetization through endorsements (e.g., Interviewee 4).

The former group of influencers—who primarily share organic content—attract followers seeking emotional connections with their posts. While they may not reap monetary benefits directly from brand endorsements, they foster deep follower engagement and achieve financial sustainability through other means. For example, Interviewee 5, a popular Japan-based Instagram influencer focused on organic motorcycle content, earns income through brand-sponsored offline events. Interviewee 7, a street basketball influencer, monetizes his online presence by operating a basketball facility that attracts his followers. Furthermore, long-form video platforms like YouTube directly reward influencers based on their content performance and viewership. These diverse revenue opportunities allow influencers who focus primarily on organic content creation to thrive and sustain their presence.

Followers of sponsorship-heavy influencers instead tend to seek curated product recommendations. They value the influencers' industry insights and ability to identify appealing offerings. Such followers accept the influencers' positioning as professional endorsers and return when seeking shopping advice or product discovery content. Conversely, influencers in the middle of the endorsement rate spectrum usually lack a clearly defined positioning. Without a clear focus, they fail to set strong audience expectations and cannot become go-to resources for emotional connection or product-related guidance. Therefore, much like human brands (Kim and Kim 2022), influencers starting out should establish a clear positioning—as either an organic content creator or a professional endorser—and develop consistent content strategies that align with that identity. For influencers who already share a mix of organic and sponsored content, it is important to recognize that engagement with their sponsored posts may decline up to a certain endorsement rate but is likely to improve after surpassing the turning point.

For marketers, our research highlights endorsement rate as a key criterion for influencer selection. Firms should prioritize influencers with clearly defined positioning, reflected in high or low endorsement rates, to maximize engagement. Contrary to conventional wisdom, frequent sponsorships do not necessarily alienate followers. As one agency representative (Interviewee 12) noted, "Professional brand endorsers and organic content creators can play complementary roles in brand promotion." High-endorsement influencers excel at creating polished content, seamlessly integrating brand messages, and driving exposure (Leung et al. 2022). Consistent with this view, our model estimates indicate that predicted engagement peaks among near-pure endorsers at the upper end of the endorsement spectrum, once endorsement rates surpass the turning point. Influencers with endorsement rates above 73% on Instagram (Study 1) and 94% on Douyin (Study 4) can sustain engagement levels at approximately 90% of the peak observed at these high endorsement rates. At the lower end of the endorsement spectrum, organic content creators focus on authenticity and trust, fostering deeper audience connections and sustained engagement (Wies, Bleier, and Edeling 2023). Predicted engagement also peaks among creators who recently began accepting sponsorships but declines as endorsement rates approach the turning point. Our estimates show that influencers with endorsement rates below 6% on Instagram (Study 1) and 5% on Douyin (Study 4) can sustain approximately 90% of this low-endorsement peak. In contrast, predicted engagement is lowest at moderate endorsement rates, with turning points estimated at 39%–48% on Instagram (Study 1) and around 52% on Douyin (Study 4), suggesting that marketers should avoid influencers in these intermediate ranges.

Average endorsement rates differ substantially across platforms, at .16 in Study 1 (Instagram) and .61 in Study 4 (Douyin). These differences reflect variation in platform content focus and monetization orientation. Despite this variation, the U-shaped pattern generalizes across platforms. On Instagram, the average endorsement rate lies well below the estimated turning point (.475 for comments and .393 for likes), which places most influencers in a favorable range for maintaining engagement. On Douyin, the average endorsement rate lies close to the estimated turning point (.519), where sponsored post engagement reaches its lowest level. Together, these patterns indicate that platform context and the location of the turning point matter for influencer selection, and brands should account for these factors when choosing influencers.

This study also presents actionable guidelines for influencers and brands seeking to navigate the U-shaped effect of the endorsement rate on consumer engagement. Influencers with moderate endorsement rates face challenges, but our findings point to a viable way to transition from low to high endorsement rates, as part of their commercial growth. For example, providing sufficient organic product mentions can help influencers increase their endorsement rate without sparking customer skepticism. One case shared by the CEO of a media company (Interviewee 10) described an influencer who built loyalty through personal stories and lifestyle content, then gradually integrated sponsored content aligned with that domain, ultimately becoming a successful lifestyle endorser. For influencers aiming to take this path, we recommend building community and trust by consistently producing content within their area of passion, while selectively accepting brand collaborations that align with that domain. Likewise, we advise marketers to analyze influencers' historical posts and endorsement patterns to identify those who demonstrate strong domain-specific passion, ensuring both authenticity and effective promotions.

Diversifying brand endorsements offers another effective content strategy for progressing from organic content creator to professional endorser. By expanding the range of their brand collaborations, influencers can signal increased brand recognition and commercial value. For brands, working with influencers who maintain either high or low endorsement rates is more likely to yield strong audience engagement, but in addition, they need to evaluate influencers' previous endorsement portfolios. Repeatedly partnering with the same influencers might offer direct benefits, as deeper collaboration can foster greater customer trust. However, both brands and influencers should recognize that cultivating a diverse portfolio of brand collaborations is essential for influencers' professional growth as they eventually increase their sponsored content, because such diversity enhances perceptions of brand recognition.

Limitations and Research Directions

Our findings offer valuable insights but also have several limitations that suggest directions for future research. First, while the endorsement rate values in our experiments align with real-world ranges observed in the field studies, differences in numerical framing may influence perceptions. For example, "2 out of 4" sponsored posts may not evoke the same response as "10 out of 20," though both represent a 50% endorsement rate. Such framing effects could alter how participants interpret the endorsement rate, and future research is needed to clarify these impacts. Second, the compensation design in Study 3 (i.e., respondents rewarded on the basis of choice compatibility) may not reflect common influencer–follower interactions, which typically are not financially incentivized. However, similar mechanisms can be observed in practice when influencers reward engaged audiences with lucky draws or giveaways. Future research could explore how alternative incentives influence consumer engagement. Third, we relied on industry standards in Studies 1 and 4 to identify sponsored content; however, influencers do not always adhere to such standards when disclosing brand partnerships (Ershov, He, and Seiler 2025). Disclosure inconsistencies may influence how audiences perceive endorsements and warrant further investigation.

Beyond addressing these limitations, we identify other promising avenues for influencer marketing research. For instance, our study focuses on examining the impact of endorsement rates on the engagement of influencers' sponsored posts. Unlike sponsored posts, organic posts carry no marketing intent or brand narratives, so mechanisms such as manipulative intent and brand recognition are less relevant. Future research could explore whether endorsement rates have a different effect on the engagement of organic posts, which may be driven by different mechanisms. Such investigations could provide a more nuanced understanding of how endorsement rates influence engagement dynamics across different types of influencer content.

The interaction between endorsement rate and brand characteristics warrants further investigation. Frequent endorsements of established brands may appear less genuine (Wies, Bleier, and Edeling 2023), whereas new brands might benefit from partnerships with professional endorsers who offer valuable, uncertainty-reducing evidence of brand recognition (Rapp et al. 2015). Finally, the rise of virtual and AI-generated influencers presents opportunities to examine how digital personas differ from human influencers in shaping engagement. Virtual influencers may appear less authentic and more manipulative due to their fictional nature (Zhou, Yan, and Jiang 2024), which could alter the effect of endorsement rates on consumer responses. Understanding these distinctions can enrich our understanding of how endorsement rates affect different types of influencers.

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Data Availability Statement

The data supporting the findings of this article are not publicly available as they were obtained from third-party data providers and are proprietary. However, they are available from the corresponding author upon reasonable request.

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