PRODUCT SALIENCE IN INFLUENCER ENDORSEMENT POSTS

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DECLARATIONS

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Abstract

Influencer endorsement posts on social media platforms such as Instagram differ regarding the salience of the endorsed product. Some posts make the product the dominant visual and narrative element, whereas others integrate it peripherally into the scene with little emphasis. We investigate how such salience of the endorsed products is related to consumer engagement on Instagram for two product categories (watches and shoes). We find that while endorsement posts with low product salience create more post engagement (i.e., likes and comments of endorsement posts), endorsement posts with high product salience create more brand engagement (i.e., likes and comments of subsequent brand-owned posts). Accordingly, the optimal level of product salience depends on the goal of the influencer campaign. As influencers aim to build their own popularity through higher levels of post engagement, the goal of the company and the goal of the influencer might not be aligned in campaigns where companies aim to drive brand engagement. We test a rich set of visual and textual product salience cues that can help managers and influencers to design endorsement posts in line with their objectives. Our research thus has important implications regarding how to design effective endorsement posts.

Keywords

Product Salience, Influencer Marketing Effectiveness, Social media, Post engagement, Brand engagement

Introduction

Influencer marketing has become a key component of digital marketing strategies (Hughes, Swaminathan, and Brooks 2019; Leung et al. 2022) and is one of the most-researched areas of social media marketing (Appel et al. 2020; Leung et al. 2022). The Influencer Marketing industry was expected to grow to $32.55 billion by 2025 with a remarkable 35.63% annual growth rate (Influencer Marketing Hub 2025). Influencers endorse branded products in their posts on social media platforms such as Instagram and TikTok to their followers, typically by visually presenting and textually providing information about the products. For followers, these endorsement posts might generate awareness, interest, and positive attitudes towards the endorsed brand that can turn into increased engagement with that brand (Leung et al. 2022) and lift sales (Beichert et al. 2024).

Recent literature on how to design effective endorsement posts has investigated how utilitarian and hedonic value (Hughes, Swaminathan, and Brooks 2019), sensory language (Cascio Rizzo et al. 2023), arousal (Cascio Rizzo et al. 2024), references to social ties (Chung et al. 2023), and sentiment (Leung et al. 2022) drive engagement (e.g., number of likes, comments, and shares) with the endorsement post. Surprisingly, none of these papers focuses on the salience of the endorsed product, which is potentially a key determinant of an endorsement post's effectiveness. While prior work investigates how sponsorship disclosure, a potential cue increasing the salience of the endorsed product, is related to engagement (Karagür et al. 2022; Cheng and Zhang 2025; Leung et al. 2022), product salience is much broader than disclosure as it is influenced by multiple features of the post, such as the visual presentation of the product, the textual information from the caption text as well as the integration of the product in the narrative of the post. Further, product salience might not primarily drive engagement with the endorsement post (which we refer to as "post engagement"), but more importantly, drive the engagement specifically directed to the endorsed product (which we refer to as "product engagement"). It might even be possible that product salience has opposing

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effects, such that it decreases post engagement but increases product engagement. As brands are ultimately interested in driving engagement towards their owned social media content (i.e., "brand engagement", defined as the number of likes and comments received by posts of the brand) to build relationships with followers, a key question arises about the extent to which engagement with influencer endorsement posts spills over to the endorsed brand (Influencer Marketing Hub 2025) and creates brand engagement.

Existing literature suggests two potential relationships between the product salience in endorsement posts and brand engagement: Prior influencer marketing literature (Eisend et al. 2020; Pan et al. 2025) suggests that product salience increases persuasion knowledge which in turn decreases engagement with the endorsement post (i.e., post engagement). Consequently, endorsement posts with high product salience may be less effective in fostering brand engagement. In contrast, the attention and decision-making literature (Meißner et al. 2020; Bhatnagar and Orquin 2022) suggests that product salience heightens attention toward the endorsed product, thereby enhancing product engagement and ultimately strengthening brand engagement. Under this perspective, endorsement posts with high product salience may still generate lower post engagement (i.e., fewer likes, clicks, and impressions), yet they can effectively engage followers with the endorsed product, potentially producing a positive spillover effect on the brand.

These two opposing processes do not allow for a conclusion as to which of the two effects prevails. Likewise, marketing practice does not seem to have a definitive answer: We asked n = 189 marketing practitioners to evaluate the expected effectiveness of two influencer posts (see Figure 1), namely, which of the two posts would lead to a higher increase in the number of followers[1] of the endorsed brand (see Web Appendix A for details). Post A (Figure 1

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[1] We use the number of followers as an indicator of brand engagement as it is simpler to evaluate since engaging (i.e., liking and commenting) with brand posts might more strongly depend on the quality and content of the brand posts.

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left) has low product salience but received relatively high post engagement (15,400 likes), while Post B (Figure 1 right) has high product salience but lower post engagement (9,371 likes). Both posts endorse a watch from the brand Cluse. 58.2% of marketing professionals preferred Post A, 37.6% preferred Post B, and 4.2% expected them to perform equally well. These results indicate low agreement among practitioners. In line with the view of the majority preferring post A, managers widely consider post engagement as an important performance metric, according to a recent survey by Influencer Marketing Hub 2025.

INSERT FIGURE 1 HERE

Against the intuition that endorsement posts with higher post engagement are most effective for the brand, even if product salience is low, we propose and empirically show that post B is more effective than post A in engaging consumers for the brand. This is because Post B generates a high level of product engagement, which subsequently strongly spills over to the brand, while Post A primarily generates a high level of post engagement, which is less likely to spill over to the brand.

To test how product salience affects post, product, and brand engagement, we collected 3,480 endorsement posts (i.e., a post made by the influencer mentioning a brand) from 555 influencers endorsing 15 brands in two product categories (watches and shoes) as well as 17,444 brand posts (i.e., a post made by the brand) from Instagram posted between February 2017 and July 2019. We investigate how textual and visual cues, that are expected to increase the salience of the endorsed product, are associated with *post engagement* (i.e., number of likes and number of comments that are not related to the endorsed product) and *product engagement* (i.e., number of comments related to the endorsed product) of the endorsement post. Our analysis indicates that product salience cues have a negative association with *post engagement* but a positive association with *product engagement*. Next, we investigate to what extent *post engagement* and *product engagement* for influencer endorsement posts drive *brand engagement* (i.e., number of

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likes and comments for brand posts). We find that the spill-over effect from product engagement to brand engagement is four times stronger than the effect of post engagement.

These results have important implications for the practical management and academic research on influencer marketing. First, we contribute to the literature on influencer post characteristics (e.g., Hughes, Swaminathan, and Brooks 2019; Leung et al. 2022; Cascio Rizzo et al. 2024) by investigating how product salience drives engagement. We find that the optimal level of product salience depends on the goal of the endorsement post. While endorsement posts with low product salience generate more post engagement, endorsement posts with high product salience generate higher product engagement, which in turn leads to higher brand engagement. While raising brand engagement is among practitioners' top stated goals for influencer marketing (Influencer Marketing Hub 2025), our survey suggests that managers are not fully aware of the relationship between product salience and brand engagement, such that our results are potentially relevant to creating more effective endorsement campaigns.

Second, based on this finding, influencers may prefer to design endorsement posts with low product salience to increase post engagement (i.e., engage their audience). As influencers generate equity by building a community of engaged followers, they are unlikely to consciously create content that is less engaging for their followers (Libai et al. 2025). As managers might give influencers a certain level of creative freedom to create endorsement posts that are perceived as authentic (Hofstetter, Lanz, and Sahni 2023; Duffek et al. 2025), influencers might create endorsement posts with low product salience that are more effective in driving post engagement yet less effective in driving product and brand engagement. To guide practitioners, our research investigates a multitude of textual and visual product salience cues on Instagram regarding their association with post, product, and brand engagement. While most of these cues are associated with lower post and higher product engagement, some cues (e.g., sponsorship disclosure) can be positively associated with both forms of engagement, while others may have

comparable strong positive associations with product engagement and only slightly negative ones with post engagement (e.g., product-post integration). These insights help managers and influencers to formulate contracts and design endorsement posts that effectively fulfill the respective campaign goals.

Third, managers should resist the intuitive explanation that endorsement posts with high post engagement are likely to be effective drivers of brand engagement. Our research shows that product salience has opposing effects on post and product engagement, such that endorsement posts either generate high post engagement or high product engagement, but not both at the same time. Therefore, when evaluating the performance of endorsement campaigns, managers might benefit from tracking how much product engagement influencers generate as well as the endorsement posts' effect on brand engagement. In addition, academics investigating the effectiveness of influencer marketing might benefit from studying product engagement as a complementary outcome of influencer marketing that is more strongly associated with brand engagement (Libai et al. 2025). For example, Chung, Ding, and Kalra (2023) conclude that endorsement posts showing a larger number of persons might be more effective as they receive more post engagement, while our findings suggest that persons distract from the endorsed product and thereby reduce product and brand engagement.

Related literature

Table 1 summarizes recent studies that investigate how endorsement post characteristics are related to post engagement on social media. Regarding the content of the endorsement posts, most studies investigate the textual features of the post. For example, Hughes, Swaminathan, and Brooks (2019) extract the functional and hedonic value of blog posts, and Leung et al. (2022) study the sentiment of a post's text. Further, Cascio Rizzo et al. (2023) show that sensory language increases post engagement, Chung, Ding, and Kalra (2023) find that referencing social

ties can increase engagement, and Cascio Rizzo et al. (2024) show that high arousal language increases engagement for micro, but decreases engagement for macro influencers. Our work extends prior research in the domain of influencer marketing by studying novel textual features that affect the salience of the endorsed product, such as the textual position of mentioning the endorsed brand and the degree to which the product is integrated within the textual story of the post.

In contrast to text, visual elements of the endorsement post are less researched in the domain of influencer marketing. Chung, Ding, and Kalra (2023) measure the number of people in influencer images as a visual indicator of social ties, finding that a higher number of people increases engagement. Additionally, other researchers use visual information to control for confounders (Cascio Rizzo et al. 2023; Cascio Rizzo et al. 2024). Our work extends prior research by studying how visual features that affect the salience of the endorsed product, such as size, centrality, contrast, and complexity of the product shown in the image, drive post and product engagement. To the best of our knowledge, none of the previous studies has investigated these visual characteristics of the endorsed product.

Research has used different operationalizations of post engagement. For example, Hughes, Swaminathan, and Brooks (2019) and Karagür et al. (2022) count the number of likes of social media posts on different platforms, while Leung et al. (2022) also consider reposts on Twitter and Weibo. As can be seen in Table 1, none of the prior studies on endorsement post characteristics studied how these characteristics affect engagement that is specifically directed towards the endorsed product (product engagement). While post engagement is a coarse signal that cannot be assigned to any specific part of a post (i.e., "likes" can be directed towards the influencer, the scenery, a specific product, and so so), product engagement signals direct consumer interest in the endorsed product. Noteworthy, post characteristics such as product salience can have opposing effects on post and product engagement, raising the need for joint investigation. Further, none of these papers has linked engagement with endorsement posts to

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subsequent engagement with the endorsed brand, a key goal of influencer marketing (Influencer Marketing Hub 2025).

<center>INSERT TABLE 1 HERE</center>

Theoretical background and hypotheses

Product salience in endorsement posts

Influencer endorsement posts on social media, and Instagram in particular, typically consist of an image that shows a situation in which the influencer interacts with or uses the endorsed product, as well as a caption that gives further information about the situation and the endorsed product. Depending on the contract between the influencer and the company, influencers are constrained in how to design the post. A recent study by Hofstetter, Lanz, and Sahni (2023) shows that text and image constraints are frequently used by managers, suggesting that managers might sometimes be skeptical that the influencer designs the post in a way that is in line with the company's expectations. Indeed, some of these constraints are closely related to product salience, such as the companies' request to "make sure that the [product/brand] is easily identifiable" (Hofstetter, Lanz, and Sahni, 2023, p. 21). Based on prior literature on influencer marketing, native advertising, and attention processes, we develop a comprehensive list of visual and textual cues of product salience and allocate them to four categories: The visual product presentation, the presence of sponsorship disclosures, the way the sponsoring brand is linked in the caption text, as well as the extent to which the product is integrated in the story of the endorsement post and the extent to which the endorsement post is integrated in the story of prior organic posts. In the following, we explain each category in detail.

Visual product presentation. To identify key visual elements that influence product salience, we refer to Orquin et al. (2020), who extensively discussed bottom-up factors that drive visual salience. In line with the authors, we focus on the visual salience of the product relative to its surroundings, which is based on the size, position/centrality, and the brightness of the object (Orquin et al. 2020). Prior research shows that making a product larger or brighter or

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presenting it more centrally in an image will direct followers' attention to it. Chandon et al. (2009), for example, tested the effect of surface size by varying the number of shelf facings on retail shelves. The authors find that brands with a larger number of facings attracted more attention and were chosen more often. In a consumer choice context, Atalay, Bodur, and Rasolofoarison (2012) show an effect of centrality on attention and choice. Testing the effect of brightness, Milosavljevic et al. (2012) provide evidence that more salient product alternatives received more attention and were more likely to be chosen.

Furthermore, considering the visual ecology of social media posts (Li and Xie 2020), we argue that the influencer's face is a unique factor of the micro-ecology of social media posts that influences product salience. In particular, we predict that an influencer's face in a posted image will decrease product salience as the face is expected to draw attention away from the product. Prior research has shown that faces are attention-grabbing stimuli (Tomalski, Csibra, and Johnson 2009); thus, the face of an influencer shown in an image should direct attention towards the influencer and away from the focal product. Several empirical studies have investigated distraction effects in the context of advertisements. Sullivan et al. (2017), for example, find that visual elements in television ads distract consumers from paying attention to risk information when presented simultaneously. Hartmann et al. (2021) show that face presence in social media posts decreased purchase intentions.

Finally, prior research shows that the visual complexity (or clutter) reduced the likelihood of consumers looking at an object (Orquin et al. 2020; Pieters et al. 2010). Complex post images consist of several visual elements that all compete for followers' attention. Rosenholtz, Li, and Nakano (2007) provide evidence that visual complexity increases response time when humans are given simple search tasks. Visschers, Hess, and Siegrest (2010) find that respondents pay less attention to nutrition labels in more complex environments. Thus, we expect that less complex images in endorsement posts will lead to more attention being paid to the endorsed product because fewer objects are competing for followers' attention.

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Sponsorship disclosure. Sponsorship disclosures are a post characteristic that stresses the promotional context of a post. While it is typically mandatory to disclose the sponsored nature of an endorsement post, the majority of paid endorsement posts might not be sufficiently disclosed (Ershov, He, and Seiler 2025). Disclosures can be included in the form of a badge (standardized disclosure; Karagür et al. 2022) or within the caption text by including phrases such as "this post is sponsored" or hashtags such as "#ad" or "#sponsored". Previous research by Guo et al. (2018) investigates the effectiveness of disclosures using eye-tracking in the context of product placements and shows that a disclosure statement increases product salience.

Brand links. Caption texts further include links to other accounts, such as the accounts of the brands that the influencer is endorsing in the post. These links help users recognize that the post endorses a product of the respective brand and thus serve as an informational cue of product salience. The attention paid to this cue likely increases the earlier in the caption it appears and decreases with a larger number of other links competing for attention.

Story integration. The caption of a post typically tells a story, describing the situation, the influencers' thoughts, as well as their feelings (Klostermann et al. 2018). The endorsed product can be integrated into the story to a varying degree (Akpinar and Berger 2017). For example, a story about "walking through Paris the whole day" could integrate a shoe product into its narrative, as walking is associated with shoes. Similarly, a story built around "forgetting the time when in Paris" could integrate a watch product, as time is associated with watches. Following Narrative transportation theory (Green and Brock 2000), we argue that integrating the product in the story of the post can help to immerse consumers in the story, which in turn increases their attention towards the endorsed product (Akpinar and Berger 2017; Wojdynski et al. 2017). Additionally, the story of the endorsement post can be integrated into the story of prior organic posts of the influencer. For example, if the influencer previously shared organic posts about her travel to Paris, an endorsement post that tells a story about Paris is more integrated than an endorsement post unrelated to Paris. We argue that products become less

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salient the more the endorsement post is integrated in the organic story of the influencer, as consumers are less likely to notice that the post is non-organic (Cheng and Zhang 2025) and are less likely to recognize the product when the endorsement post looks similar to its surroundings (Aribarg and Schwartz 2020).

Product salience and endorsement post engagement

Prior literature on native advertising in the domain of YouTube videos (Akpinar & Berger, 2017) and website banners (Aribarg and Schwartz, 2020; Wojdynski and Evans, 2015) has documented that higher salience of the advertised product leads to fewer shares and clicks of the ad. Similarly, Li and Xie (2020) and Hartmann et al. (2021) find that posts without a face, potentially increasing the attention directed to products, receive lower engagement. These initial empirical results suggest that the salience of products can reduce post engagement.

One theoretical explanation for a possible negative effect of product salience on post engagement is the activation of persuasion knowledge (Friestad and Wright 1994). It can be argued that product salience directs consumer attention to the endorsed product, which in turn activates knowledge about the influencer's persuasion attempt. Consumers can cope with persuasion knowledge in several ways, but skepticism and reactance are prevalent (Isaac and Grayson 2017). While some consumers might have a positive reaction to influencers' persuasion attempts, either because they are grateful for receiving information about new products or because they perceive it as fair when the influencer earns money, most consumers might value influencers' intrinsic motivations and non-commercial orientation (Audrezet et al. 2020; Pan et al. 2025). In line with this argument, prior research has shown that influencers lose followers (Cheng and Zhang 2025) and engagement (Karagür et al. 2022; Eisend et al. 2020) when consumers observe that posts are sponsored by companies. Consequently, we expect that:

H1: Product salience has a negative effect on post engagement.

The effect of product salience on product engagement is less clear to hypothesize based on prior literature. On the one hand, product salience and its effect on persuasion knowledge

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can lead to resistance and lower credibility, also negatively affecting the attitude towards the endorsed product and the associated brand (Eisend et al. 2020; Pan et al. 2025). However, product salience also drives attention to the endorsed product, which could counteract and even exceed the negative effect of persuasion knowledge. The attention and decision-making literature suggests that visual attention affects preference accumulation in favor of choice options (e.g., Armel et al. 2008; Cavanagh et al. 2014; Krajbich et al. 2010; Newell and Pelley 2018; Towal et al. 2013). A recent meta-analysis by Bhatnagar and Orquin (2022) confirms that attention has a causal effect on preferences and choice. Moreover, the decision-making and marketing literature documents a close coupling of attention allocation and preference formation and choice (e.g., Krajbich et al. 2010; Meißner et al. 2020; Milosavljevic et al. 2012; Shimojo et al. 2003). In all, this literature stream suggests that product salience can increase engagement with the endorsed product. Consequently, we expect that:

H2: Product salience has a positive effect on product engagement.

The theoretical explanations underlying our hypotheses are summarized in the conceptual model presented in Figure 2. While we have so far hypothesized the effect of product salience cues on post and product engagement, it is important to note that some cues might not only affect engagement through the proposed attention-persuasion knowledge path but also act as a signal of source credibility (Pan et al. 2025). For example, sponsorship disclosure might signal transparency (Cao and Belo 2024; Boerman 2020; Karagür et al. 2022), and integrating the endorsed product in the story of the endorsement post, as well as integrating the endorsement posts in the story of the organic posts of the influencer, could increase authenticity of the endorsement (Duffek et al. 2025). In addition, posts not showing the face of the influencer might not only increase attention towards the product, but at the same time feel unrelatable (Duffek et al. 2025). It seems therefore plausible to assume that some visual and textual elements of product salience affect post and product engagement beyond the hypothesized product salience path.

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INSERT FIGURE 2 HERE

Effect of endorsement post on brand engagement

We understand brand engagement as interactions between consumers and content created by brands on social media (Lee, Hosanagar, and Nair 2018), such as liking or commenting on posts of a brand or following the brand account. Brand engagement is an important marketing asset that has been shown to impact sales and shareholder value (Kumar et al. 2016; Colicev et al. 2018). When consumers follow a brand page on social media, it is likely to result in higher levels of in-store purchases (Mochon et al. 2017). Prior research has started to investigate how brands can generate their own content that is more engaging (see Liadeli, Sotgiu, and Verlegh 2023 for a meta-analysis), but this research lacks insights into how influencer endorsement posts can help to increase brand engagement.

Engagement for influencer endorsement posts can spill over to brand engagement in several ways. First, the endorsement post can raise awareness for the brand for consumers not aware of the brand or not aware of the Instagram account of the brand. Second, influencers often endorse new products that consumers might not be aware of, such that the endorsement post raises their interest in the brand's offerings. Besides awareness, endorsement posts might evoke interest or even a more positive attitude towards the brand, as consumers might trust the opinion and follow the taste of influencers they are following. All these processes would explain why engagement with endorsement posts should positively spill over to engagement with subsequent brand posts. Following our conceptual model (Figure 2), we distinguish post and product engagement, and propose that both spill over to brand engagement with varying strength.

To generate post engagement, consumers must interact with an endorsement post, and it is therefore plausible to assume that they elaborate on the content of the post to a certain extent when this interaction takes place. While this elaboration might or might not include paying attention to the endorsed product, it is straightforward to predict that endorsement posts

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with higher post engagement lead to higher brand engagement, as each interacting consumer is exposed to the endorsed product. This notion is reflected in the multitude of influencer marketing research using post engagement as a measure of effectiveness (see Table 1).

In contrast to post engagement, product engagement requires a consumer to mention the endorsed product or brand in a comment (e.g., "I like the watch you are wearing!"). Therefore, a consumer must have paid attention to the endorsed product and elaborated on the endorsement. If the comment has a positive sentiment, the consumer likely has a positive attitude towards the endorsed product, which corresponds to a more advanced stage in the consumer decision journey. Thus, product engagement is more likely to spill over to brand engagement. Hence, we predict that both post and product engagement will drive brand engagement, but that the effect of product engagement should be stronger.

H3a: Post engagement has a positive effect on brand engagement

H3b: Product engagement has a positive effect on brand engagement

H3c: The effect of product engagement on brand engagement will be stronger than the effect of post engagement on brand engagement

Empirical setting

The empirical setting considers influencer Instagram posts endorsing brands as well as posts created by these brands on their own accounts. We focus on studying how consumers interact with these posts. The behavioral process underlying our observations can be described as follows: consumers observe influencer posts where a particular product is endorsed. Consumers might pay attention to the endorsed product and become interested, which we cannot observe. However, we can observe whether consumers interact with the post by liking or commenting on it (post engagement) or writing a comment referring to the product (e.g., "the watch looks great!"; product engagement). In the next step, consumers might want to learn more about the brand and visit its Instagram account. While we do not observe whether a specific

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consumer visits the account of the brand at the individual level, at the aggregate level, however, we can observe how many consumers interact with the posts of the brand by liking or commenting on them (brand engagement).

We will formulate and estimate two models: an influencer-engagement model and a brand-engagement model (see Figure 3). First, the *influencer-engagement model* seeks to explain increases in post and product engagement for influencer endorsement posts as a function of product salience cues. Next, the *brand-engagement model* seeks to explain increases in brand engagement as a function of aggregate post and product engagement, which we refer to as spill-over effects. The reason for estimating two separate models is that the post and product engagement from multiple endorsement posts may spill over to the engagement of an individual brand post. Accordingly, when modeling brand engagement, we need to aggregate post and product engagement for multiple endorsement posts related to the same brand. We therefore sum up the number of likes, comments, and product-related comments for all influencers posts endorsing the particular brand before a particular brand post. The brand-engagement model will help us to determine how post and product engagement spill over to brand engagement.

INSERT FIGURE 3 HERE

Sample

To study the proposed relationships, we built a sample of Instagram influencer endorsement posts for two product categories: watches and shoes. These categories are suitable for our study, given that they represent products often promoted by influencers. Influencity (2025), for example, emphasizes that the beauty and fashion industry is a standout leader in the influencer marketing market. Further, both products can be accurately detected in images, and we expect sufficient variation regarding the visual presentation. Since both products are relatively small, influencers can, for example, set visual product salience very high (i.e., an image showing only the product) or low. Additionally, there are several brands focusing their

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product portfolio on one of these categories, which allows us to better link endorsement posts with brand engagement. It further allows us to identify the product in the endorsement post that belongs to the respective brand (i.e., if a brand that predominantly sells watches is linked in an endorsement post showcasing a watch, it's probable that the watch depicted in the image belongs to that brand, rather than any other item visible in the picture). To collect a sample of influencer endorsement posts, we started with a sample of 3,359 influencer accounts by searching influencer names mentioned in blog posts using the Google search query "influencer list". To minimize survivorship bias (i.e., certain influencer traits might increase the probability of being listed), we also collected accounts from influence.co, a large community in which influencers create profiles to connect with sponsoring brands. While these accounts might suffer from self-selection bias (i.e., certain influencer traits might increase the probability of creating an account), we argue that using both samples helped us study a broader set of influencers than using only one of the two. While brands sometimes mention[2] influencers they collaborate with in their brand posts (i.e., "@[influencer account name]"), these influencer accounts are potentially selected by the brand based on performance, such that a sample of these accounts could be biased with respect to our analysis. Further details on the sample collection and descriptive statistics are given in Web Appendix B. For each influencer, we downloaded Instagram posts between February 2017 and July 2019 (130 weeks) and counted the number of linked brands (i.e., a brand is linked in an Instagram post by adding "@[brand account name]" in the caption text).

Considering the 500 brands mentioned most often by the influencers, we then identified all brands that primarily sell either watches or shoes. For our study, we used a sample consisting of five watch brands and 11 shoe brands (see Table 2). From the raw sample of 5524 posts

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[2] At the time of collecting the data, it was not possible to collect all public posts that mention a specific account.

mentioning one[3] of the selected brands, we remove 309 (5.59%) posts with a video because the visual attention of the endorsed object is not comparable to a single image. Furthermore, we only considered influencers with multiple endorsement posts, which allowed us to estimate a model with influencer fixed effects. We removed 339 (6.50%) posts from influencers with a single post.

We then downloaded the images for all endorsement posts mentioning any of the aforementioned brands and detected all objects and faces in the image using the Google Cloud Vision API (Google 2020a). At the time of computing, the underlying model was based on a deep convolutional neural network (InceptionV3) and returned a list of object names and object locations for all objects and faces detected in the image. The API is very accurate when applied to brand-related content and has therefore been used in several recent marketing articles (e.g., Klostermann et al. 2018; Li and Xie 2020).

After annotating all 4,876 posts, we kept those in which the product in question (i.e., watch or shoe) was detected. After annotating the images, we observed that smaller objects were sometimes not classified correctly. One reason could be that the underlying model rescales input images to 299 × 299-pixel images, which makes it complicated even for humans to identify small objects (Google 2020b). To make sure that all objects were found, we partitioned the original images into 299 × 299-pixel segments, as this is the required size for the input matrix of the InceptionV3 architecture. Partitioning the images revealed 943 images with products that had not been detected when only applying the Google Vision API to the original-sized images. We advise future research to keep this in mind when detecting small objects. Notably, the watch (shoe) objects we identified occupied an average of 3.27% (shoe: 7.69%) of an image (calculated as the ratio of the number of pixels of the object to the number of pixels

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[3] In 25 cases, influencer endorsement posts mentioned more than one brand from our sample, for example a watch and a shoe brand. From the mentioned brands, we randomly selected the brand that we assigned the post to.

of the full image). In total, 3,480 (out of 4,876; 71.37%) images posted by 555 influencers remained in the sample as the respective product was detected. A research assistant manually annotated 100 randomly selected images from the set of images in which a watch was detected and 100 randomly selected images from the set of images in which no watches were detected but a watch brand was endorsed. In the former sample, all the images depicted a watch. In the latter, eight images contained watches that had not been detected by the API, indicating an acceptable accuracy rate. In all eight cases, the watch object was hardly visible and easily mistaken for a bracelet. The 555 influencers in our final sample capture a wide range of popularity with numbers of followers between 3,761 and 41 million (M = 541,699, SD = 2,347,649).

INSERT TABLE 2 HERE

On average, we observed 6,273 endorsement posts per influencer (SD = 9,465). In the next steps, for all brands in the influencer post sample, we downloaded all brand posts from Instagram (i.e., all posts that the brands post on their own channel). In total, 17,444 posts were extracted for the period between February 2017 and July 2019. Table 2 gives an overview of the influencer endorsement and brand posts.

Influencer-engagement models

The influencer-engagement models aim to empirically measure the impact of product salience cues on post and product engagement for influencer endorsement posts. The models are estimated based on the sample of n = 3,480 influencer posts endorsing one of the sampled watch or shoe brands. In the following, we first describe the variables of interest and our identification strategy before we show the model formulation and model results.

Variables

Post and product engagement. We categorize the number of interactions an influencer's post receives into two classes: *Product engagement* refers to each interaction that can be clearly identified as related to the endorsed product. This includes all comments in which the text of the comment is related to the endorsed product, as explained below in detail. *Post engagement* refers to all other interactions where it is not clear if they are related to the product or not. We measure post engagement according to the number of likes and the number of comments that do not refer to the endorsed product, similar to most prior studies in influencer marketing (see Table 1; e.g., Hughes, Swaminathan, and Brooks 2019). As the number of likes is typically much larger than the number of comments, the variance in post engagement is mostly driven by the number of likes.

While we cannot infer what drives a "like" (e.g., the influencer, the content of the post, or the displayed product), comments can refer to a specific element of the post. Since we focus on two specific product categories (i.e., watches or shoes), comments that mentioned the product (e.g., "I like your watch", "Fancy shoes!") can be interpreted as engagement related to the endorsed product. We consequently count all comments that include a keyword related to the product category: "watch" and "wristwatch" for the watch category, and "shoe", "boots", "heels", "slippers", "sneakers", "sandals", "moccasins", "trainers", and "pumps" for the shoe product category. We translated the keywords into more than 15 common languages to account for non-English comments. Product engagement is then computed as the number of comments that include at least one keyword. We manually checked 200 randomly chosen comments that included a keyword, and in all cases, the keyword referred to the product. However, we recognize that in rare cases, the keywords might have other meanings. We further count all comments that included the name of the endorsed products' brand as product engagement because consumers might sometimes use the brand name to refer to the product (e.g., "Fancy vans!" instead of "Fancy shoes!").

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We further evaluate the sentiment of the comments to assess how consumers relate to the product (e.g., positive or negative). Two research assistants evaluated 250 randomly sampled comments by inferring the attitude of the comment writer towards the product on a 7-point Likert scale (1 = "very negative"; 7 = "very positive"). Inter-rater agreement was high (Kendall's W = .749). We found a mean attitude of 6.014 (SD = .716) with 98.8% of the comments classified as "slightly positive" or better. Therefore, we argue that our measure of product engagement does not need to be corrected for sentiment. On average, endorsement posts in our sample have a post engagement of 12,872 (SD = 40,953) and product engagement of 4.395 (SD = 11.512). See Figure 4 for a visual example of the dependent variables and product salience cues that are explained in the following.

INSERT FIGURE 4 HERE

Visual product presentation. We considered the following visual cues: the visual salience of the product relative to its surroundings (based on the size, position/centrality, and the brightness of the product), face presence, and visual complexity. We used the information retrieved by the Google Cloud Vision API to operationalize product size (relative size of the product object) and product centrality (one minus the Euclidean distance between the center of the image and the center of the product object). Several methods are available for measuring the brightness of objects (Borji and Itti, 2013). We chose the adaptive whitening saliency (AWS) method proposed by Garcia-Diaz et al. (2012), as it outperforms comparable models in predicting where observers look (Borji and Itti 2013). The AWS algorithm can be used to compute a salience map that assigns a salience value for each pixel of the original image. We averaged the salience values for the area of each object detected by the API in the image and then calculated the product brightness as the ratio between the endorsed object brightness (i.e., the average pixel AWS score in the area of the image in which we detected the endorsed watch or shoe) and the AWS score of the object with the highest AWS score. We then averaged the standardized values for product size, product centrality, and product brightness to compute the

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visual salience of the product. Further, we measure the presence of a face (1 = image contains a face; 0 = else), as faces potentially grab attention and distract from the product (Tomalski, Csibra, and Johnson 2009). 49.8% of the posts show at least one face. Table 3 shows example images for both product categories, high and low visual salience, and face.

INSERT TABLE 3 HERE

Third, we measure visual complexity using the clutter measure proposed by Rosenholtz et al. (2007). The measure reflects how difficult it would be to add a new object to the image that would reliably draw attention. Accordingly, products are less likely to receive attention the more complex the image.

Sponsorship disclosure. We investigated two forms of sponsorship disclosure that differ in terms of visibility, namely standardized and textual disclosure. A standardized disclosure appears above the post (Figure 4, see label "6") and follows the standardized format "Paid partnership with [brand]" (Boerman 2020). In contrast to other forms of disclosure, standardized disclosure is verified by the sponsoring brand. 10.8% of the posts have a standardized disclosure. The most common form of sponsorship disclosure is textual disclosure, wherein the influencer discloses sponsorship somewhere in the text (Figure 4, see label "7"). This form of disclosure typically includes the addition of an indicator word (e.g., sponsored) or a tag (e.g., #sponsored) to the post. We created a set of indicator words (Web Appendix C) and matched them with the text of a post to measure textual disclosure. In our sample, 36.3% of the posts have a textual disclosure.

Brand links. All caption texts in our sample included a link to the brand (@[brand]) the influencer was endorsing. Because the brand link is a cue driving attention towards the product, its position should impact its visibility. We measured the brand link position as a binary variable that reflects whether the cue is within the first two lines of the caption text (Position of brand mention = 1) or not (Position of brand mention = 0). Placing the cue at the beginning of the caption increases the visibility of the cue, as followers might stop reading the caption after the

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first line. Additionally, Instagram typically displays the first two lines of the caption in the mobile view (i.e., using the smartphone app), while the rest of the caption only becomes visible when the consumer expands the text. We further count the number of links in the caption as well as the number of links in the image (Figure 4, see label "9"). Note that the links in the image are only shown when the user taps the button in the lower right corner.

Story integration. Captions differ regarding the degree to which the endorsed product is integrated into the story of the post (product-post integration) and the degree to which the story of the post is integrated into the story of prior organic posts (post-organic integration). To calculate product-post integration, we map the text of the caption as well as the category-name (i.e., "watch" or "shoe") into a multidimensional embedding vector using all-mpnet-base-v2 (Song et al. 2020), a model known for its strong performance in semantic similarity and information retrieval tasks. We remove the brand name from the caption, as popular brands might have semantic similarity to the category. We next calculate the cosine distance between the caption embedding and the category-name embedding. Looking at the example post from Figure 4, the caption "on mondays we stay at laduree and never stop ordering more" shows a distance of .874 to the category name "watch", while the alternative caption "time always flies by at laduree" reduces the distance to .817 and "wearing my new watch at laduree" to .648. We multiply this distance by -1 to compute product-post integration. To validate the measure, a research assistant, blind to the study's objectives, annotated ("The product is an integral part of the story of the caption text"; 1 = "strongly disagree to 7 = "strongly agree") the captions of 80 posts. These posts were selected via a stratified random sample, balanced across the two product categories and quartiles of the story integration distribution. We find a reasonable correlation between the annotation and the proposed measure of r = .616. Similarly, we measure how strongly the story of the focal endorsement post is integrated into the prior organic posts the influencer shared (post-organic integration). To do so, we measure the average cosine distance

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between the caption of the endorsement post to all captions of the last 10 posts[4] before the endorsement posts (see Cheng and Zhang 2025 for a similar measure). We multiply this distance by -1 to compute post-organic integration.

All main variables are summarized in Table 4. In our sample, 49.8% of the posts show a face, 36.3% indicate their sponsored nature in the caption, and 10.8% use a standardized sponsorship disclosure. On average, influencers link 2.42 other accounts in their caption, and for 51.5% of the posts, the endorsed brand account is linked at the beginning of the caption.

INSERT TABLE 4 HERE

Identification

To identify and empirically measure the relationship between product salience cues and post and product engagement, we accounted for several factors that could bias our estimates. We do so by adding fixed effects for influencers, brands, and time as well as a rich set of potential confounders as control variables, by correcting for algorithmic targeting, and by modeling the selection probability of an influencer to endorse a specific brand.

Fixed effects. We included fixed effects for each influencer, endorsed brand, week, and weekday to control for differences in our dependent variables as a function of these dimensions. Influencer fixed-effects account for the variance between influencers (e.g., attractiveness, expertise, and number of followers), such that our estimates reflect changes in engagement between different posts of the same influencer that vary in terms of product salience cues. Endorsed-brand fixed effects likewise control for differences between brands that are constant over time, such as different social media strategies or product positioning. Week and weekday fixed effects account for time-varying effects that might confound the estimates, such as Cyber Monday Week.

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[4] Models with 5,7, and 15 last posts show similar results.

Control variables. We control for a set of potential cofounders, some of which have also been used in prior studies. Using the image of the post, we control for colorfulness and brightness of the image (Lie and Xie 2020). Using the text of the caption, we control for the length of the text, the number of exclamation and question marks, as well as the number of hashtags. We also compute the caption sentiment using the VADER method by Hutto and Gilbert (2014). Further, we inferred whether the post included a coupon or giveaway based on a set of keywords depicted in Web Appendix C. We also control for the number of prior endorsement posts, as influencers might learn how to set the optimal level of product salience. We added the Google trend of the endorsed brand to control for time-varying interest in the brand. Further, the content of the image might drive engagement, and the salience of the endorsed product might be correlated with specific content. To control for the content of the image, we utilized the objects detected in the images. We represented each image as a vector of object-size scores for all objects in the dataset (159 different objects in total). We added 8 factors with an eigenvalue greater than one as control variables to the model. For example, the first factor has high loadings for the objects "orange," "lemon," and "tableware," and thus indicates that the image depicts a table with objects. We refer to these factor-score variables as visual-content fixed effects.

Algorithmic targeting of posts. Social media algorithms try to optimize engagement by targeting consumers (i.e., they show content to consumers who are more likely to engage; Costine 2018; Lee et al. 2018). Although Instagram shows each post to each follower, the order of posts is not chronological; rather, it is determined by the targeting algorithm. This ordering may also influence post and product engagement. According to Instagram (Costine 2018), algorithmic targeting is based on (a) how recently the post was published, (b) past consumer engagement with the sender of the post, and (c) past consumer engagement with similar content. To control for (a) how recently the post was published, we recorded the time between the post and the subsequent post in hours. Other things being equal, the algorithm determines the post

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order according to recency. To control for (b) past consumer engagement with the sender (e.g., the brand or the influencer), we defined a metric of abnormal prior post engagement. If prior posts received more engagement, the algorithm is likely to send the focal post to more consumers who engaged with the prior posts. To account for abnormal engagement of similar posts, we weighed the abnormal engagement of prior posts by their similarity to the focal post by measuring the Jaccard similarity between the respective posts' texts[5]. To test whether these three variables are indeed related to algorithmic targeting, we collaborated with a brand in the entertainment industry that shared information on post reach (i.e., number of consumers who see the post) with us. We found that recency (.029, p < .01), abnormal prior post engagement (.042, p < .001), and abnormal similar post engagement (.056, p < .001) significantly explain a post's reach. Details can be found in Web Appendix E.

Strategic selection of influencers. Brands implementing an influencer marketing campaign will likely be strategic in selecting influencers and scheduling endorsement posts. Unobserved factors might simultaneously explain influencers' posts and product engagement. We addressed this issue by applying the Heckman selection model proposed by Hughes, Swaminathan, and Brooks (2019), which has also been used by Leung et al. (2022) and Wies, Bleier, and Edeling (2023) in the domain of influencer marketing (Heckman 1979). Let s_{kt} denote an endorsement dummy variable equal to 1 if influencer k is endorsing a brand in week t. To capture the unobserved characteristics that explain this selection, we estimate a probit model with s_{kt} as a function of the number of influencers similar to k that endorse a product from the same category (i.e., watches or shoes) in the same week (n_{kt}). The model further includes influencer and week fixed effects to control for time-invariant changes in selection probability between influencers or time-variant changes that affect selection for influencers in general (e.g.,

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[5] Our dataset does only include the images of the posts explained in Table 2. We calculate the Jaccard similarity as the number of words that appear in both the focal post and a prior post divided by the number of all words that appear in the focal and the prior post.

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weeks before Christmas). In our analysis, influencers similar to influencer k are those that co-appear with influencer k most often (i.e., the highest number of times the influencer endorses a product from the same category in the same week). The probit model shows a significant effect of n_{kt} on s_{kt} (.880, p < .01). We add the inverse Mills ratio (IMR) as a control variable to our models. Details of the probit model are described in Web Appendix F. Despite all these efforts to identify the causal relationship between drivers of product salience and engagement, it is worth mentioning that the results should be interpreted carefully with respect to causality.

Model formulation

Since our metrics of post and product engagement are non-negative integers exhibiting overdispersion, we used a negative binomial regression such that:

$$\ln(E[\text{post\_engagement}_{ik}]) = \beta_0 + \beta_1 \text{Product\_salience}_{ik} + \beta_3 \text{Control}_{ik} \qquad (1)$$

$$\ln(E[\text{product\_engagement}_{ik}]) = \gamma_0 + \gamma_1 \text{Product\_salience}_{ik} + \gamma_3 \text{Control}_{ik} \qquad (2)$$

where post_engagement$_{ik}$ denotes the sum between the number of likes and comments not referencing the product of post i by influencer k. Likewise, product_engagement$_{ik}$ denotes the number of product-related comments. Product_salience$_{ik}$ is a vector containing all product salience cues (see Figure 4). Control$_{ik}$ is a vector of control variables, as well as influencer, endorsed brand, week, and weekday dummies

Model results

All results for post engagement and product engagement are summarized in Table 5 and discussed in the following paragraphs. Web Appendix G shows specifications without control variables, without fixed effects, and using a linear model with a log-transformed dependent variable. Variance inflation indices are between 1.92 and 4.61 (M = 2.74) for the main explanatory variables.

Product salience cues. The visual salience of the product has a negative association with post engagement (–.022, p = .023) but a positive one with product engagement (.330, p <

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.001). Images with a face have higher post engagement (.121, p < .001) but lower product engagement (–.360, p < .001). Lastly, visual complexity is linked to higher post engagement (.022, p = .011) but lower post engagement (–.123, p < .001).

Regarding the textual design elements, standardized disclosure has a significant positive association with post engagement (.075, p = .018) and product engagement (.655, p < .001). Textual disclosure has a significantly positive association with product engagement (.158, p = .010), and a non-significant positive association with post engagement (.014, p = .499). Linking the brand directly at the beginning of the caption has a negative association with post engagement (–.072, p < .001) but a positive association with product engagement (.216, p < .001). Linking many brands in the caption text is positively associated with post engagement (.122, p < .001), but negatively with product engagement (–.215, p = .014). Linking more brands in the image is not-significantly associated with more post engagement (.019, p = .193) but significantly associated with less product engagement (–.118, p = .207).

When the product is more integrated into the post's story, the post received non-significantly less post engagement (–.011, p = .207), but significantly more product engagement (.180, p < .001). However, when the story of the post is more integrated into the story of prior organic posts, the endorsement posts received more post (.024, p = .036) but not significantly less product engagement (–.050, p = .139).

Taking all product salience cues together, a clear pattern emerges: Endorsement posts with higher product salience generate less post engagement but more product engagement. These results support H1 and H2. A notable exception is sponsorship disclosure, which has a positive relationship with post and product engagement. While we hypothesized a positive effect on product engagement, one explanation for the positive association with post engagement could be that sponsorship disclosure signals transparency (Cao and Belo 2024).

INSERT TABLE 5 HERE

Control variables. All three variables we used to control for algorithmic targeting, recency (.038, p < .001), abnormal prior post engagement (.075, p < .001), and abnormal similar post engagement (.026, p = .004) exert a significant association with post engagement but no significant association with product engagement. This is consistent with our expectation that the algorithm relies on these factors when sorting posts. Influencer selection (i.e., inverse Mills ratio) significantly affects post (.042, p = .018) and product engagement (−.196, p < .001), confirming the importance of controlling for it. Text length has a negative association with post engagement (−.060, p = .003). In addition, questions are associated with more product engagement (.335, p < .001). Posts with a giveaway incentive gained more post (.140, p = .007) and product engagement (.859, p < .001). This effect could partially stem from instructions that create product-related comments (e.g., "To participate, write a comment why you like the product"). When endorsing brands that are trending on Google, influencer posts gained more post (.085, p = .087) and product (.326, p < .032) engagement. The number of prior product endorsement posts has a negative association with product engagement (−.155, p = .032). This indicates a wear-out effect whereby multiple exposures to the same product category could reduce followers' product engagement.

Model robustness. We next aim to test the robustness of the results. All results are depicted in Web Appendix G. Table G1 shows results for nested models explaining post engagement with only product salience variables (M1) and including all control variables besides fixed effects (M2). We also test log-linear models (M3). The same models are tested for product engagement (M4 to M6). All estimates are very similar to those reported in Table 4. Next, we test a model where we remove outliers in post engagement (i.e., post engagement lower than 5% or higher than 95%-quantile of the distribution) to rule out that the results are driven by extreme values (Table G2, M1, and M2). The results look very similar to Table 4, with visual product salience exerting a slightly less strong association with post engagement (-.005, p > .10). Next, the estimates might be strongly driven by over-represented brands in our

sample, such as Daniel Wellington (see Table 2). We weigh observations by the inverse of the total number of observations per brand. The results again look very similar (Table G2, M11, and M12).

Brand-engagement model

The brand-engagement model aims to present evidence on whether high post and/or product engagement in the context of influencer endorsement posts actually transfers to higher brand engagement on Instagram.

Variables

Brand engagement. We measure brand engagement as the number of likes and comments received by a brand post. This measure captures two processes: First, consumers need to see the brand post, which on Instagram either indicates that they are following the brand account and see the post in their home feed or that they see the brand post in the explore feed, which is a selection of posts ordered by the targeting algorithm. Second, consumers are likely to pay at least some attention and interest in the content before interacting (Lee et al. 2018). Thus, our measure reflects two goals of influencer marketing, namely, increasing brand awareness and brand engagement. While the number of followers of the brand account might also reflect engagement to some extent, it is less clear if these followers engage with the brand's content or if they ignore it but have not unfollowed the brand account.

Aggregate post and product engagement. To measure aggregate post engagement, we count the number of likes and comments not referring to the endorsed product/brand of all influencer posts endorsing brand j in week t, where week t is the week of brand post i. For Aggregate product engagement, we count the aggregate number of comments referring to the endorsed product of all influencer posts endorsing brand j in week t.

Carryover effects. Brand engagement is likely to be affected not only by influencer post and product engagement from the week of the brand post but also from all prior influencer

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endorsement posts, as consumers' decision to visit the brand page on Instagram might be made at a later stage, and consumers who once engaged with the brand might do so again in later weeks. To account for such carryover effects, we define aggregate post engagement and aggregate product engagement as stock variables such that:

$$\text{Stock}_{ijt} = \lambda \text{Stock}_{ij,t-1} + Z_{ijt}, \tag{3}$$

where Z_{ijt} denotes either post or product engagement for post i of brand j in week t (Koyck 1954). The parameter λ explains the size of the carryover effect, with higher values indicating a stronger spillover from week t–1 (i.e., one week before the week of post i) to week t. We used a grid search to test all values of λ between .01 and .99 in steps of .01 and recorded the models' Bayesian information criterion (BIC). We found that λ =.65 minimizes the BIC of the model. A recent meta-analysis by Köhler et al. (2017) found a very similar carryover effect for targeted advertising. Using a stock formulation also reduces the potential reverse effect from brand engagement on post and product engagement, as we assume that consumers do not strongly engage with historic content (i.e., content posted before subscribing to an account).

Identification

As we use field data from Instagram, we acknowledge that omitted variables and several sources of endogeneity might affect our estimates. Hence, estimating the effect of influencer post and product engagement on brand engagement requires several issues to be addressed. Similar to the post engagement model, we do so by adding control variables, by correcting for algorithmic targeting, and by modelling the selection probability of an influencer to endorse a specific brand. Further, we use instrumental variables for post and product engagement.

Control variables, algorithmic targeting, and influencer selection. Regarding the image of the brand post, we control for image colorfulness, image brightness, inclusion of a face, as well as visual complexity. For caption text, we control for length, number of exclamation marks, question marks, hashtags, and number of links. We compute the caption sentiment and classify captions as coupons and giveaways. We further add the Google trend of

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the brand, as well as the number of prior brand posts, to the model. The model includes fixed effects for brand, week, and weekday. All variables are operationalized the same way as in the influencer-engagement models. Additionally, we add the same variables to control for algorithmic targeting (recency, abnormal prior post engagement, and abnormal similar post engagement). To control for influencer selection, we average IMR for all influencers endorsing brand j in week t.

Instrumental variables. Regarding the use of instrumental variables, we use a control function approach (Papies, Ebbes, and Heerde, 2017). The two potentially endogenous variables are aggregate post and product engagement. This endogeneity may arise from unobserved factors (e.g., other marketing campaigns that the brand runs outside of social media) that simultaneously boost engagement with the endorsement posts of the influencers and the posts of the brand. Instruments for these two variables must be relevant (i.e., strongly related to post and product engagement) and valid; that is, they should not directly cause changes in the dependent variable, brand engagement, of the second stage model after all other variables are controlled for. As instrumental variables, we first used the average post engagement (i.e., average number of likes) of all posts a particular influencer k created in week t (i.e., the week before the endorsement post) that were not endorsing brand j. The average number of likes for these posts should be correlated with post engagement for the endorsement post since it reflects how strongly influencers have recently been in contact with their followers (relevance). Further, because non-endorsement posts should be unrelated to brand j, engagement with these non-endorsement posts should not affect engagement with posts made by the brand, except through its impact on the engagement with the endorsement post (exclusion restriction). The prior posts could be organic posts not endorsing products (e.g., selfies of the influencer) or, while less common in our data, endorsements of other brands.

To control for the endogenous variance in product engagement (i.e., number of comments referring to the endorsed product), we used the average number of comments of all

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posts created by a particular influencer k in week t that were not endorsing brand j. We argue that this is a relevant instrument, as more comments reflect that followers are more likely to elaborate on the content of the post by adding a comment. As in the case of the first instrument, the average number of comments on prior posts should not drive brand engagement, as the prior posts were unrelated to the brand.

Using this set of instruments in a first-stage model, we regressed the two drivers of interest for brand engagement (aggregate influencer post and product engagement) on the two instrumental variables and all other variables from the brand-engagement model. Formally, we estimated a negative binomial regression model with $\ln(E[y_{ijt}]) = \beta_0 + B_1 X_{ijt} + B_2 U_{ijt}$, where y_{ijt} is either the aggregate influencer post or product engagement for post i of brand j in week t, X_{ijt} contains all other regressors from the main model, and U_{ijt} is a matrix of instrumental variables. We denote by φ_{ijt} the residuals of these first-stage models. Accordingly, in the second stage, we included the Pearson (i.e., raw residuals divided by the standard error of y_{ijt}) residuals $\widehat{\varphi}_{ijt}^{Post}$ and $\widehat{\varphi}_{ijt}^{Product}$ from these first-stage models as regressors to control for the endogenous variance of the main variables of interest. Note that post and product engagement, as well as the two instruments, are stock variables as described above. Results for first-stage models with instrumental variables are shown in Web Appendix H., Table H1.

INSERT TABLE 6 HERE

After estimating the parameters, we found a significant relationship between the two instruments and aggregate post engagement as well as aggregate product engagement (Table 3). In line with our expectation, aggregate post engagement is positively affected by the number of likes of prior non-endorsement posts (1.072, p < .001). Further, influencers seem to generate less post engagement when their prior non-endorsement posts received more comments (−.060, p < .001). For aggregate product engagement, the effects are the other way around. An interpretation for the negative effects is that influencers create content that is either able to

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generate likes or comments, but not both at the same time. For the post-engagement model, including the instrumental variables increases Nagelkerke's pseudo R^2 from .633 to .983. For the product engagement model, Nagelkerke's pseudo R^2 increases from .700 to .827. Thus, the instruments are relevant. We consequently used the residuals $\widehat{\varphi}_{ijt}^{Sender}$ and $\widehat{\varphi}_{ijt}^{Product}$ from both models as control variables in the main model.

Variable descriptions for the brand-engagement model are summarized in Table 7. Variable correlations and descriptive statistics for the brand-engagement model are depicted in Web Appendix I.

INSERT TABLE 7 HERE

Model formulation

The brand-engagement model relies on a negative binomial regression model such that:

$$\ln(E[\text{Brand\_engagement}_{ijt}]) = \alpha_0 + \alpha_1 \text{ Aggregate\_post\_engagement}_{ijt} + \qquad (4)$$
$$\alpha_2 \text{ Aggregate\_product\_engagement}_{ijt} +$$
$$\alpha_3 \text{ Control}_{ijt}$$

Where $\text{Brand\_engagement}_{ijt}$ denotes the brand engagement (i.e., the number of likes and comments) of post i by brand j in week t. $\text{Aggregate\_post\_engagement}_{ijt}$ counts the aggregate number of likes and comments not referring to the endorsed product/brand of all influencer posts endorsing brand j in week t, where week t is the week of brand post i. $\text{Aggregate\_product\_engagement}_{ijt}$ counts the aggregate number of comments referring to the endorsed product of all influencer posts endorsing brand j in week t. As before, as brand engagement is a non-negative integer with overdispersion, we use the negative binomial regression model (Li and Xie 2020). Control_{ijt} is a vector of control variables as well as brand and time fixed effects. All variables are explained in the following section.

Results

All results for brand engagement are summarized in Table 8 and discussed in the following paragraphs. Web Appendix J shows specifications without control variables, without fixed effects, and using a linear model with a log-transformed dependent variable.

Endorsement post engagement. The results show a significant positive spill-over effect of aggregate post engagement (.014, p < .001) and aggregate product engagement (.055, p < .001) on brand engagement. In terms of magnitude, however, product engagement shows a four times higher association with brand engagement, indicating that influencer posts that generate high levels of product engagement are better suited to drive brand engagement. These findings are in line with H3a, H3b, and H3c.

Control variables. Abnormal prior post engagement (.044, p < .001) and abnormal similar post engagement (.064, p < .001) show a significant positive association with brand engagement. Influencer selection has a significant effect (–.036, p < .001). Further, posts including a face get less engagement (–.046, p < .01). Regarding the caption text we observe that caption length (–.041, p < .001), number of hashtags (–.083, p < .001), and number of links (–.054, p < .001) have a negative association with engagement, while posts with more question marks (.092, p < .001) and posts including a giveaway (.640, p < .001) get more engagement. As expected, brands get more engagement the more people search for them on Google (.425, p < .001). This finding indicates that the Google trend was able to capture interest in the brand due to, for example, other campaigns and events. We also observe that the number of prior posts has a negative effect (–.061, p = .003).

INSERT TABLE 8 HERE

The results conclude that brand engagement is strongly driven by influencer posts that create high levels of product engagement and less by influencer posts that create post engagement. Based on the estimates from the Influencer-engagement model and the Brand-engagement model, in the next section, we seek to simulate how changes in product salience affect brand engagement via decreased post and increased product engagement.

Simulation

To illustrate the magnitude of the estimated effects and to connect the influencer-engagement model and the brand-engagement model, we estimated the expected post and product engagement for two simulated influencer endorsement post that differ regarding the product salience cues that were shown to have significant opposite effects (i.e., visual salience, face, visual complexity, brand link position, number of links in caption, and number of links in image). For the "High product salience" post, we set the above-mentioned variables that have a positive association with post engagement to their 10%-quantile levels, while the variables that have a negative association with post engagement are set to their 90%-quantile values. For the "Low product salience" post, we do the opposite. We then estimate the expected association with post and product engagement compared to a post where all variables are set to the 50%-quantile. Next, we use the expected values to estimate the expected association with brand engagement. As shown in Figure 5, varying the product salience cues changes the expected post and product engagement, and in turn the expected brand engagement.

INSERT FIGURE 5 HERE

In the simulated example, the "Low product salience" post would lead to an estimated brand engagement decrease of –7.84% compared to the median post, while the "High product salience" post leads to a brand engagement increase of 3.60% compared to the median post and an increase of 11.4% in comparison to the "Low product salience" post.

General discussion

Influencers endorse brands on social media by showcasing and describing the brands' products both visually and through text in their posts. This paper is the first to systematically study how the salience of the endorsed product drives consumer engagement processes with the endorsement post and, subsequently, with the brand sponsoring the post. We analyze ten product salience cues for influencer endorsements endorsing watch and shoe products on Instagram,

and find a clear pattern: Posts with high product salience receive less post engagement, but create more product engagement. While both post engagement and product engagement spill over to brand engagement, product engagement exerts a four times stronger association with subsequent brand engagement. Based on these findings, endorsement posts with high (vs. low) product salience translate into a 12% higher increase in brand engagement.

Theoretical contributions

Our research contributes to the research on influencer marketing in several ways. First, we contribute to the knowledge on influencer endorsement post design (Hughes, Swaminathan, and Brooks 2019; Cascio Rizzo et al. 2024; Cao and Belo 2024) by investigating how the salience of endorsed products is related to consumer engagement. Product salience emerges as a double-edged sword, increasing consumers' engagement with the endorsed product but decreasing the overall engagement with the influencer post. These findings suggest a trade-off that has previously been documented in other forms of native advertisement, such as website banners (Aribarg and Schwartz 2020) and video ads (Akpinar & Berger 2017): Brands and influencers have to trade off how much engagement an advertisement generates (post engagement) against how much engagement is dedicated to the advertised product (product engagement). In this sense, product salience cues can be used to reallocate consumer engagement between the post, the product endorsed in the post, and the endorsed brand.

These findings advance our understanding of trade-offs in influencer marketing and help to bridge the gap between influencer marketing and prior literature on native advertising for display ads (Aribarg and Schwartz 2020; Wojdynski and Evans 2015; Wojdynski et al. 2017).

Second, our research advances the literature on sponsorship disclosures. While prior research has come to different conclusions regarding how sponsorship disclosure affects post engagement (Karagür et al. 2022; Leung et al. 2022; Cao and Belo 2024), we find a positive effect that is stronger for standardized disclosure badges than for disclosures within the caption text (e.g., #ad). More importantly, we find that disclosures also have a positive effect on product

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engagement, as they potentially increase attention towards the endorsed product. In this sense, disclosures are the only product salience cue that does not induce a trade-off, but boosts both post and product engagement. This finding indicates that the trade-off might be stronger for cues increasing salience through conspicuity (e.g., visual salience, face, brand link position) than for those increasing salience through transparency, such as disclosing the paid partnership.

Third, the present research contributes to the literature on engagement processes in the context of influencer marketing. First, our study reveals that product salience is substantially related to engagement creation, but the effect depends on which form of engagement is considered: Higher product salience has a negative association with post engagement, but a positive association with product engagement that, in turn, leads to higher brand engagement. Thus, our study confirms that not all forms of engagement are equal, supporting Leung et al.'s (2022, p. 112) argument that "even if generating consumer engagement (e.g., likes, comments, reposts) is a primary objective of influencer marketing campaigns, not every form of engagement is created equal." Our findings, therefore, contribute to the literature on engagement processes on social media and influencer marketing specifically.

Managerial implications

Our findings have several important implications for influencers on image-centric platforms such as Instagram, as they design endorsement posts and choose how saliently to display the endorsed product, as well as companies collaborating with these influencers, as they draw contracts with specific constraints regarding the design of the endorsement posts. Our results reveal that product salience cues can be used to reallocate consumer engagement across the influencer post, the specific product endorsed in the influencer post, and the brand that collaborates with the influencer. This reallocation can imply goal misalignment between influencers and companies: For companies, the optimal level of product salience depends on the goal of the campaign. If the goal is to create endorsement posts that generate high levels of interactions, impressions, and reach, low product salience is beneficial. If the goal is to engage

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consumers with the offered product, high product salience helps. As our study reveals that product engagement is much more likely to spill over to the brand, increasing product salience might be preferable from the brand perspective. For influencers, they have to strike a balance between post and product engagement: While engaging their audience with posted content reflects their social capital (Libai et al. 2025), being able to effectively engage their audience for branded products potentially translates into higher compensation by brands.

Our initial survey provides evidence that managers might not be fully aware of these relationships. When deciding which influencer post they expect to increase brand engagement, the majority decided on a post with high post engagement, even though product salience was very low. Our results cast doubt on this decision. Further, not only do the managers we surveyed prefer endorsement posts with high post engagement. A recent survey by Influencer Marketing Hub (2023) also finds that managers widely consider post engagement with the influencer post (e.g., number of clicks, likes, and comments) as the most important performance metric. If the goal of the endorsement post is to drive brand engagement, we advise managers not to solely focus on post engagement.

Despite the general tendency of product salience cues to drive product and impair post engagement, our research documents ten product salience cues that differ in strength and have asymmetric effects on post and product engagement. For example, increasing the visual product salience has a strong positive effect on product, while only a moderate negative effect on post engagement. Similarly, integrating the product in the caption post mainly affects product engagement, and integrating the endorsement post into the story of prior organic posts mainly affects post engagement. These results help companies and influencers to design endorsement posts that achieve a good balance of post and product engagement.

In addition, sponsorship disclosure drives both post and product engagement, potentially because it boosts transparency and credibility (Karagür et al. 2022). While recent research indicates that influencers often avoid disclosure of sponsored posts (Ershov, He, and Seiler

2025), it is less clear if this happens because influencers anticipate lower post engagement for disclosed posts or because brands anticipate lower product and brand engagement. However, independent of the reason, our research indicates that disclosures drive all forms of engagement without a trade-off that occurs for other forms of salience cues. Thus, our findings imply that disclosures are helpful, increasing both transparency and product attention.

Finally, our findings also have important ethical implications. Some product salience cues can enhance transparency for consumers by making the commercial nature of influencer posts more apparent. For example, product salience cues such as sponsorship disclosure or mentioning the brand at the beginning of the caption text help consumers to sense the commercial nature of the post. In line with empirical results demonstrating the positive effects of sponsorship disclosure via increased perceived transparency (Karagür et al. 2022), endorsement posts with high product salience reduce the risk of blurring the line between native influencer content and advertising. Therefore, product salience not only contributes to achieving marketing objectives but also upholds ethical standards of transparency.

Limitations and further research

Our study is subject to several limitations that pave the way for future research. First, while we study how product salience drives engagement of individual influencer posts, investigating the effectiveness of influencer campaigns that consist of multiple endorsement posts and multiple influencers would allow us to derive further important insights for theory and practice. For example, it might be effective to start a campaign with low product salience to build post engagement and then increase product salience to turn the increased attention into product engagement. Similarly, a campaign with a portfolio of influencers might be more effective when some influencers present the product with high, and others with low, product salience. Similarly, investigating outcomes besides brand engagement, such as awareness and sales, would yield a more holistic assessment of how to set product salience (Libai et al. 2025).

Second, we focused on two product categories (watches and shoes) from the beauty and fashion industry that are very popular in influencer content. This sector thrives on high involvement and visual appeal, making it a perfect fit for social media (Influencity 2025). However, it would be interesting to test if our findings translate to low involvement products that are less likely to trigger persuasion knowledge. Further, product salience could be less relevant in categories where products are very salient by default (e.g., cars) or where products are not visually tangible (e.g., services), but it could also be more relevant for content formats where attention is short (e.g., stories and reels). Future research should therefore investigate additional product categories that are less visually tangible and for which product presentation on social media—as well as the effects of visual salience—may operate differently.

Third, our study currently focuses on Instagram, which is an image-centric platform where posts include images and text. However, many other platforms, such as YouTube and TikTok, strongly focus on video content. While the visual elements of product salience we studied can be applied to videos on a frame level (Schwenzow et al. 2021), motion and voice might drive additional attention to the product.

Further, some of the investigated drivers could interact such that in the presence of one driver, others become less important. For example, when testing whether product salience is moderated by face (Web Appendix G, Table G2), we find that including a face can mitigate (.41, p < .05) the negative effect of product salience on post engagement (−.034, p < .01). This result indicates that visual product salience does not exert a negative association with post engagement when faces make the post perceived as more personal.

Fourth, a valuable tactic for influencers may be to change the visual aesthetic of endorsement posts during the growth and evolution of their social media career. Increasing post engagement seems to be particularly important when starting a new social media channel, as studies show that creating post engagement is an essential mechanism that helps influencers to build their follower base. Similarly, influencers might not only endorse products from

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companies but also start to endorse their own products. In this case, product salience might affect both post and product engagement positively. We anticipate that high product salience may no longer trigger the same level of persuasion knowledge or reactance because the influencer's commercial intent is more transparent and integrated into their personal brand identity. Future research is necessary to investigate how product salience affects engagement in these scenarios.

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PRODUCT SALIENCE IN INFLUENCER ENDORSEMENT POSTS

FIGURES
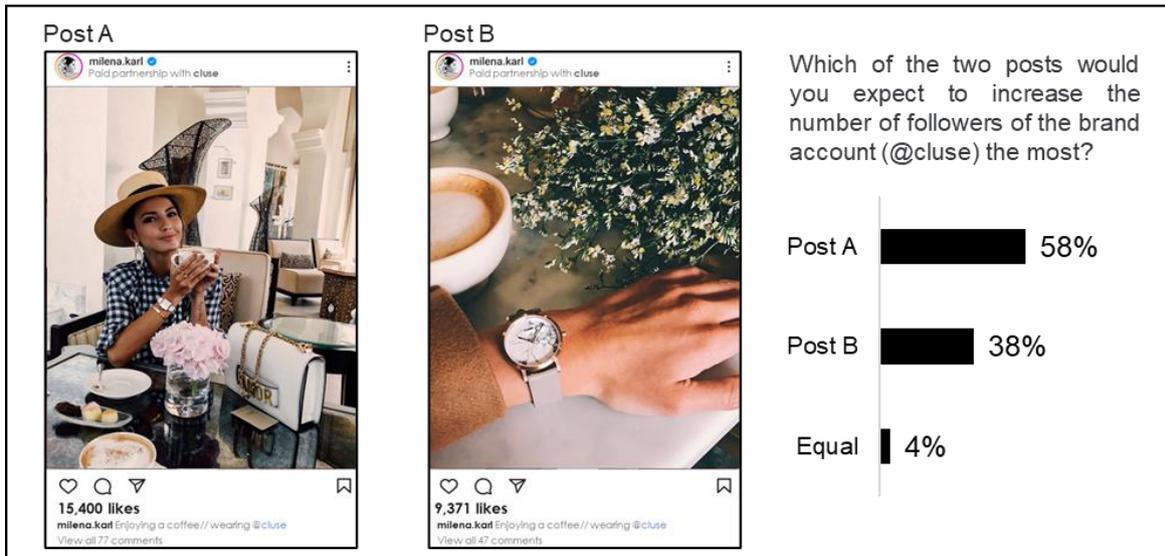
Figure 1. Managers' expectations of endorsement post effectiveness.

Notes: A survey with marketing managers (n = 189) shows that most managers expect that Post A (Low product salience, high post engagement) leads to more followers than Post B (High product salience, low post engagement). See Web Appendix A for full post and survey details.
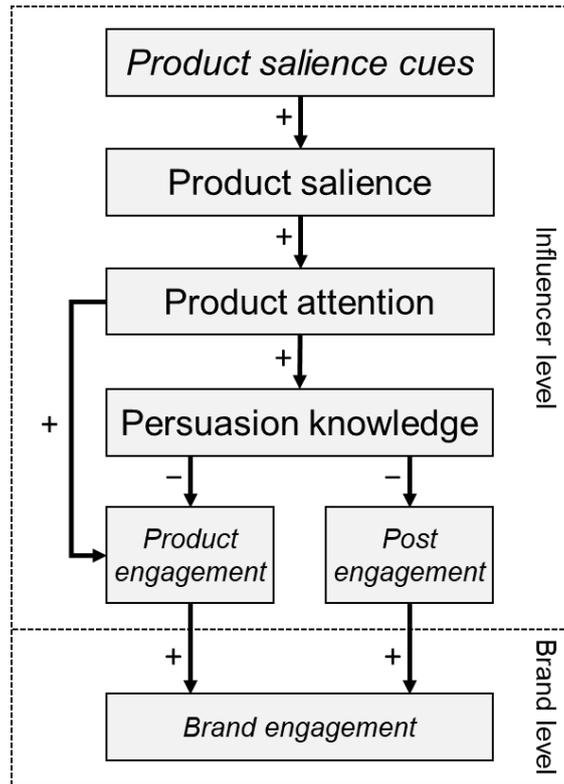
Figure 2. Conceptual model

Notes: Measured concepts in italics.
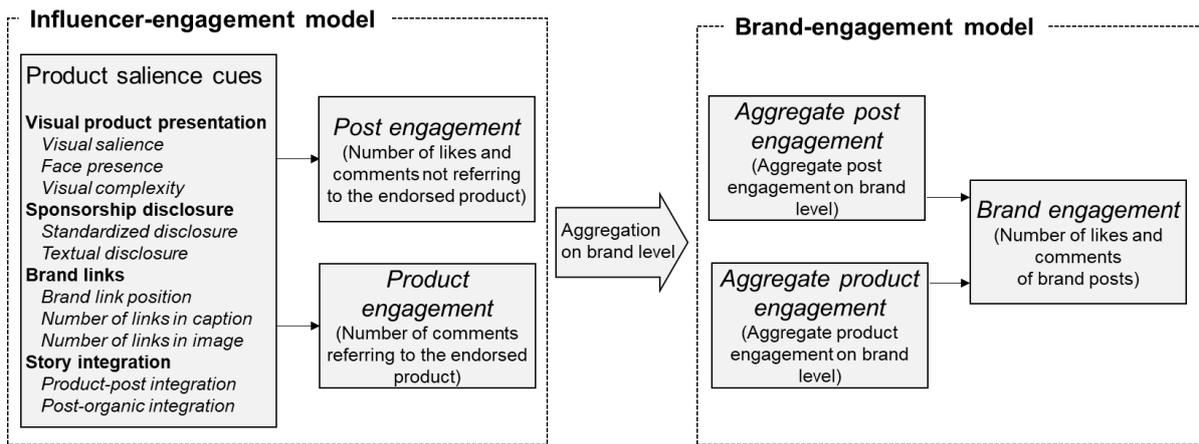
Figure 3. Empirical framework.

Notes: Variable names are in italics.

Figure 4. Dependent variables and product salience cues for the influencer-engagement models

Notes: 1) Post engagement; 2) Product engagement; 3) Visual salience; 4) Face; 5) Visual complexity; 6) Standardized disclosure; 7) Textual disclosure; 8) Brand link position/number of links in caption; 9) Number of links in image; 10) Product-post integration and post-organic integration.
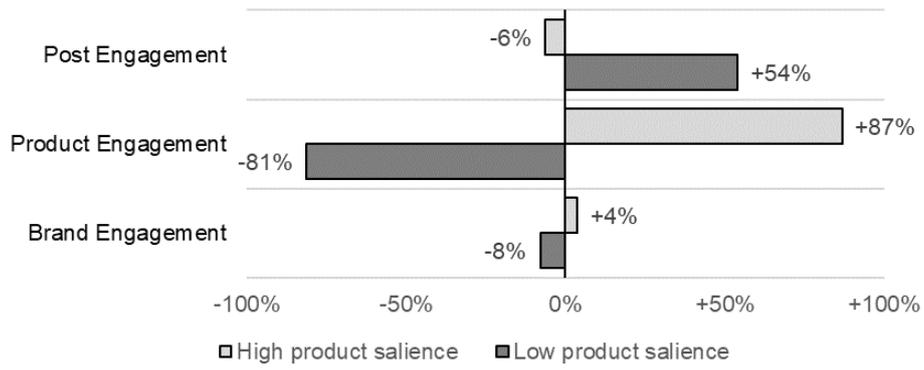
Figure 5. Effect of product salience on post, product, and brand engagement

Notes: Values are percentage changes compared to a post with median product salience.

PRODUCT SALIENCE IN INFLUENCER ENDORSEMENT POSTS

TABLES

Table 1. Prior research on influencer endorsement post characteristics and engagement

Authors	Platform	Investigated post characteristics	Dependent variable Engagement with…		
			Post	Product	Brand
Hughes, Swaminathan, and Brooks 2019	Blog, Facebook	Campaign type; Expertise; Hedonic value; Campaign incentive	✓		
Karagür et al. 2022	Instagram	Sponsorship disclosure	✓		
Leung et al. 2022	Weibo	Sentiment; Sponsor salience; New product launch	✓		
Chen, Yan, and Smith 2022	Bilibili	Sponsorship disclosure; Early brand appearance; Customization; Subjectivity	✓		
Cascio Rizzo et al. 2023	Instagram, TikTok	Sensory language	✓		
Chung, Ding, and Kalra 2023	Instagram	Post reference to close social ties	✓		
Cascio Rizzo et al. 2024	Instagram, TikTok	Aroused language	✓		
Cao and Belo 2024	Facebook, Instagram	Sponsorship disclosure	✓		
This study	Instagram	Product salience	✓	✓	✓

<div align="center">**Table 2.** Sample description</div>

Category	Brand	Number of influencer endorsement posts	Number of brand posts
Shoes	Aldo	158	1,468
	Allbirds	14	890
	Asics	48	449
	Dr. Martens	90	1,535
	Hunter Boots	32	712
	Louboutin	159	1,227
	Puma	242	446
	Skechers	51	481
	Toms	39	511
	Vans	211	976
Watches	Cluse	594	1,752
	Daniel Wellington	1,331	2,414
	Fossil	182	732
	Kapten and Son	219	2,295
	Mvmt	110	1,556
Sample size:		n = 3,480 (Sample for influencer-engagement models)	n = 17,444 (Sample for brand-engagement model)

Table 3. Example images for visual salience

Category:	Watch		Shoe	
Visual salience:	High	Low	High	Low
With face				
Without face				

Table 4. Main variables descriptions for influencer-engagement model

Variable	Description	Mean[a]	SD[a]
Dependent variables			
Post engagement	Number of likes and comments not referring to the endorsed product.	12,872	50,952
Product engagement	Number of comments referring to the endorsed product/brand.	4.395	11.512
Visual product presentation			
Visual salience	Composite measure of the standardized measures for endorsed product visual size, centrality, and brightness.	.000	2.127
Face	Binary variable; = 1 if the post shows at least one face.	.498	.500
Visual complexity	Visual complexity measure from Rosenholtz et al. (2007).	3.656	.518
Sponsorship disclosure			
Standardized disclosure	Binary variable; = 1 if the post contains a standardized disclosure badge.	.108	.310
Textual disclosure	Binary variable; = 1 if the post caption contains a textual disclosure (e.g., #ad).	.363	.481
Brand links			
Brand link position	Binary variable = 1 if the link to the endorsed brand is in the preview of the caption text.	.515	.500
Number of links in caption	Number of "@" characters of the caption (log).	2.418	2.648
Number of links in image	Number of accounts linked in the image of the post (log).	4.766	5.778
Story integration			
Product-post integration	Semantic similarity between caption text and endorsed product category	−.811	.083
Post-organic integration	Mean semantic similarity between caption text and caption texts of the last 10 posts.	−.682	.109

Notes: Values are calculated before log transformation. All variable correlations and descriptives are shown in Web Appendix D.

Table 5. Results for the influencer-engagement model

Dependent variable:	Post engagement		Product engagement	
Product salience cues				
Visual salience	−.022**	(.010)	.330***	(.030)
Face	.121***	(.020)	−.360***	(.060)
Visual complexity	.022**	(.009)	−.123***	(.027)
Standardized disclosure	.075**	(.032)	.655***	(.093)
Textual disclosure	.014	(.021)	.158**	(.062)
Brand link position	−.072***	(.019)	.216***	(.057)
Number of links in caption	.122***	(.027)	−.215**	(.087)
Number of links in image	.019	(.015)	−.118**	(.046)
Product-post integration	−.011	(.009)	.180***	(.026)
Post-organic integration	.024**	(.011)	−.050	(.034)
Algorithmic targeting				
Recency	.038***	(.010)	.018	(.030)
Abnormal prior post engagement	.075***	(.009)	.030	(.026)
Abnormal similar post engagement	.026***	(.009)	−.031	(.028)
Influencer selection				
Inverse Mills ratio	.042**	(.018)	−.196***	(.050)
Control variables				
Image colorfulness	−.001	(.008)	−.037	(.026)
Image brightness	.002	(.009)	.009	(.026)
Caption length	−.062***	(.021)	−.025	(.065)
Caption exclamation marks	−.001	(.017)	−.043	(.053)
Caption question marks	.037	(.024)	.335***	(.069)
Caption hashtags	−.008	(.025)	.001	(.076)
Caption sentiment	.001	(.009)	.032	(.028)
Coupon	−.016	(.026)	.016	(.077)
Giveaway	.140***	(.052)	.859***	(.149)
Google trend endorsed brand	.085*	(.050)	.326**	(.152)
Number of prior endorsement posts	−.034	(.024)	−.155**	(.072)
Fixed effects				
Influencer		Yes		Yes
Endorsed brand		Yes		Yes
Week		Yes		Yes
Weekday		Yes		Yes
Visual content		Yes		Yes
Nagelkerke R^2		.963		.623

Notes: ***p < .01, **p < .05; *p < .10. N = 3,480. Standard errors in parentheses.

Table 6. Results for first-stage models with instrumental variables

Dependent variable:	Aggregate post engagement		Aggregate product engagement	
Average log(likes) of non-endorsement posts	1.072***	(.005)	−.675***	(.015)
Average log(comments) of non-endorsement posts	−.060***	(.006)	1.530***	(.020)
Nagelkerke R^2	.983		.827	
Nagelkerke R^2 without instrumental variables	.633		.700	

Notes: *** $p < .001$. The models include all variables later used in the second-stage model. N = 17,444. Standard errors in parentheses.

Table 7. Main variables descriptions for the brand-engagement model

Variable	Description	Mean[a]	SD[a]
Brand engagement (Dependent variable)	Number of likes and comments for each brand post	25,364	38,810
Aggregate post engagement	Aggregate number of likes and comments not referring to the endorsed product/brand for posts of all influencers endorsing the brand in the week of the brand post (log-transformed). Stock variable with a carryover coefficient of λ =.65.	31,784	79,038
Aggregate product engagement	Aggregate number of comments referring to the endorsed product/brand for posts of all influencers endorsing the brand in the week of the brand post (log-transformed). Stock variable with a carryover coefficient of λ =.65.	13	31

Notes: Values are calculated before log transformation. Variable correlations and descriptive statistics for the brand-engagement model are depicted in Web Appendix H.

Table 8. Results for the brand-engagement model

Dependent variable:	Brand engagement	
Constant	7.895***	(.144)
Endorsement post engagement		
Aggregate post engagement	.014***	(.003)
Aggregate product engagement	.055***	(.007)
Control functions		
$\widehat{\varphi}^{Sender}$	−.010**	(.004)
$\widehat{\varphi}^{Product}$	−.023***	(.005)
Algorithmic targeting		
Recency	.003	(.004)
Abnormal prior post engagement	.044***	(.005)
Abnormal similar post engagement	.064***	(.004)
Influencer selection		
Average Inverse Mills ratio	−.036***	(.005)
Control variables		
Image colorfulness	.0004	(.004)
Image brightness	−.007	(.004)
Face	−.046***	(.011)
Visual complexity	−.002	(.004)
Caption length	−.045***	(.01)
Caption exclamation marks	.015	(.014)
Caption question marks	.092***	(.017)
Caption hashtags	−.083***	(.010)
Number of links in caption	−.054***	(.012)
Caption sentiment	.022***	(.005)
Coupon	.031	(.051)
Giveaway	.640***	(.038)
Google trend Brand	.425***	(.018)
Number of prior brand posts	−.061***	(.021)
Fixed effects		
Brand	Yes	
Week	Yes	
Weekday	Yes	
Nagelkerke R^2	.841	

Notes: ***p < .01, **p < .05; *p<.10. N = 17,444. Standard errors in parentheses.

PRODUCT SALIENCE IN INFLUENCER ENDORSEMENT POSTS

Web Appendices

Introduction text:

Welcome to the survey!

Imagine you work as a marketing analyst at the watch brand Cluse. Cluse has the goal to increase the number of followers of its owned Instagram account (@cluse). The brand therefore collaborates with the influencer Milena.karl, a fashion influencer with many followers on Instagram. Milena endorses the brand on her own account through a post in which she is wearing a watch from Cluse and linking to the account of Cluse (@cluse).

On the following page, you see two posts created by Milena.karl. The posts differ regarding
- **how the product is presented** and
- **how much engagement (likes and comments)** they receive.

Please look at the post and all the information in detail!
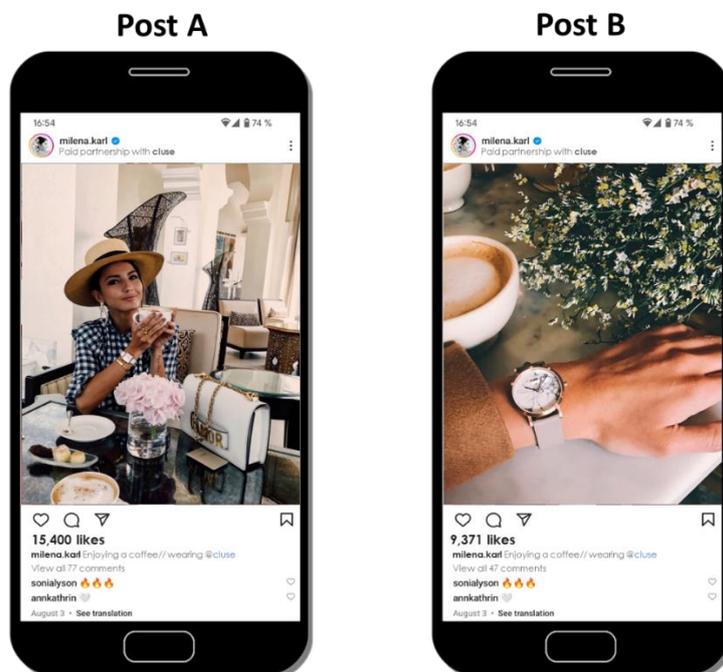
Which of the two posts would you expect to increase the number of followers of the cluse account (@cluse) the most?
- Post A (58.2%)
- Post B (37.6%)
- Equally (4.2%)

Briefly explain your choice
- Open ended text

Which of the following areas describe your work in your organization? You can choose multiple areas.
- Social media management (19%)
- Marketing (30%)
- Product management (20%)
- Project management (12%)
- Communications (18%)
- Finance (7%)
- Human Ressources (7%)
- Accounting (4%)
- Legal (1%)
- Analyst (8%)
- Other (30%)

Please evaluate your professional experience regarding the following topics on a scale from 0 = "very unexperienced" to 100 = "very experienced".
- Marketing (M = 49.904; SD = 28.548)
- Social Media (M = 53.867; SD = 29.255)
- Influencers (M = 35.762; SD = 28.028)
- Performance metrics (M = 49.598; SD = 29.465)
- Instagram (M = 50.310; SD = 33.003)

Web Appendix B: Sample Details

Before building a sample of sponsored influencer posts related to a specific product category (i.e., watches), we considered several issues to avoid selection bias. First, on Instagram, posts can be found by searching for a username or hashtag; however, hashtags are not standardized. Identifying brand-related posts by #[brand] would not have allowed us to generate a representative sample, as the probability of using a hashtag might depend on characteristics of the post or the influencer, generating a self-selection bias. Second, to find usernames associated with influencer accounts, one can use a brand page and collect a list of influencers mentioned in the brand posts. For example, several watch companies use images created by paid influencers and repost the content on their own accounts, mentioning the influencer with @[influencer name]. However, brand managers might tend to select only highly engaging influencer posts to repost on their brand's channel, which could generate selection bias. To avoid the aforementioned selection effects, we first built a set of influencer accounts, collected their posts, and analyzed which brands were mentioned in these posts; then, we focused on a set of brands belonging to the product categories watches and shoes considered exemplary.

We focused on two sources of data: First, we ran a Google search for websites that list influencer names. Google search queries "[category] influencer list" with the categories fashion, beauty, travel, fitness, and cooking were used to account for a wide range of areas of expertise. We then collected all account names from the top 50 websites proposed by Google that contained lists of influencer names. As these websites are mostly organized as recommendations on whom to follow, they can be assumed to focus on popular or successful influencers. Therefore, we also used the influencer community influence.co to extend this list of influencer accounts. At the time of collecting the data in 2019, more than 100,000 influencers were using this network to connect with brands and initiate sponsorship relationships. We

assumed a self-selection bias for less popular influencers who utilized the community to establish themselves as potential collaborators for brands. In total, we collected 1,430 accounts from the Google search and 1,914 additional accounts from the community search, while an additional 303 accounts from the community search were already present in the Google search dataset. From a merged list of 3,344 influencer accounts, we collected all Instagram posts posted between February 2017 and July 2019.

The key influencer characteristics—number of total posts, number of followers at the time of collecting the data, and proportion of verified influencer accounts (i.e., accounts with a blue verified badge to ensure account authenticity)—are summarized in Table A1. As expected, influencer accounts in the community sample were less popular (in terms of number of followers) than in the Google search sample (p <.01). Additionally, influencers from the community sample had fewer posts (p < .01) and were less likely to be verified (p < .01) than the sample with all accounts. The number of followers ranged from 830 to 131,699,474, with a median of 90,024, indicating that the sample included both micro- and macro-influencers.

Table B1. Social media influencer characteristics

Sample	Variable	Mean	Median	Min.	Max.
All accounts	Posts	1,691	1,168	101	40,005
(n = 3,344)	Followers	1,262,592	90,024	830	131,699,474
	Verified	31%			
Google search	Posts	1,890	1,322	101	40,005
accounts	Followers	2,753,207	393,058	1,025	131,699,474
(n = 1,430)	Verified	58%			
Community	Posts	1,543	1,060	102	23,528
search accounts	Followers	148,914	55,714	830	4,778,717
(n = 1,914)	Verified	11%			

Web Appendix C: Indicator Words

Table C1. Indicator words

Variable	Indicator words
Textual disclosure	"advert", "advertisement", "advertising", " ad ", "sponsored", "sponsorship", "#ad ", "#advert", "#advertising", "#sponsored", "#spon", "[ad]", "/ad ", "/advert", "sponsored", "advert ", "advertisement", " ad/"
Type: Promotion	"coupon", "code", "% discount", "$ off", "% off", "% "
Type: Giveaway	"giveaway", "competition", " give away", "giving away"

Web Appendix D: Variable Correlations and Descriptive Statistics for Influencer Engagement Model

Table D1. Influencer engagement model – Variable correlations

No.		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	Post engagement	1	.061	-.028	.087	-.031	.173	-.023	.046	.041	-.073	-.066	-.051	.018	-.018	-.033	-.019	.017	-.007	-.050	-.043	-.023	-.033	-.039	-.060	-.001	.002	-.011
2	Product engagement	.061	1	.135	-.096	-.069	.073	.119	.070	-.082	-.058	.112	-.041	.012	.035	-.020	.015	-.036	-.024	.005	.014	.029	.017	.054	.078	.178	.005	-.032
3	Visual conspicuity	-.028	.135	1	-.337	-.230	-.004	.018	.224	-.182	-.215	.136	-.097	-.020	-.094	-.091	-.076	-.032	.034	-.109	-.008	-.025	-.001	-.060	.101	-.007	.041	.018
4	Face	.087	-.096	-.337	1	.128	.142	-.014	-.026	.018	-.008	-.004	-.062	.040	.035	.018	.150	-.076	-.071	-.059	-.030	.015	-.048	-.011	-.164	-.005	.064	-.091
5	Visual complexity	-.031	-.069	-.230	.128	1	.012	.026	-.025	-.108	.053	-.054	.023	-.003	.052	.034	.066	.131	.192	-.050	-.021	.046	-.001	.024	-.063	-.029	-.048	-.102
6	Standardized disclosure	.173	.073	-.004	.142	.012	1	.069	.040	-.128	-.092	-.004	-.032	.018	-.027	-.078	-.046	-.024	-.051	-.061	-.021	.021	-.037	.013	-.058	-.001	.050	.020
7	Textual disclosure	-.023	.119	.018	-.014	.026	.069	1	-.016	-.215	-.073	.065	.014	.073	.040	-.043	.089	.020	.021	.078	.141	.087	.093	.189	.287	.015	.033	-.126
8	Brand link position	.046	.070	.224	-.026	-.025	.040	-.016	1	-.284	-.161	.217	-.246	-.037	-.053	-.057	-.055	-.018	-.021	-.469	-.181	-.191	-.092	-.251	-.045	-.070	-.003	-.045
9	Number of links in caption	.041	-.082	-.182	.018	-.108	-.128	-.215	-.284	1	.368	-.099	.325	-.079	.008	.140	-.116	-.068	-.055	.462	.016	-.020	-.054	.078	-.200	.143	.076	.320
10	Number of links in image	-.073	-.058	-.215	-.008	.053	-.092	-.073	-.161	.368	1	-.012	.271	-.066	.067	.141	-.112	-.002	.011	.197	-.020	.004	-.019	.047	-.089	.004	.014	.238
11	Product-post integration	-.066	.112	.136	-.004	-.054	-.004	.065	.217	-.099	-.012	1	-.069	-.020	-.050	.013	.068	-.064	.002	-.132	-.027	-.042	-.110	-.026	.011	.015	.052	-.040
12	Post-organic integration	-.051	-.041	-.097	-.062	.023	-.032	.014	-.246	.325	.271	-.069	1	-.101	.069	.144	-.167	-.049	.037	.363	.076	.053	.077	.121	-.061	.074	.028	.249
13	Recency	.018	.012	-.020	.040	-.003	.018	.073	-.037	-.079	-.066	-.020	-.101	1	-.014	-.020	.143	.049	.016	.008	.042	-.006	.006	.043	.137	-.022	-.049	-.140
14	Abnormal prior post engagement	-.018	.035	-.094	.035	.052	-.027	.040	-.053	.008	.067	-.050	.069	-.014	1	.364	.004	.047	.036	.056	.047	.020	.023	.092	.038	-.005	-.029	-.049
15	Abnormal similar product engagement	-.033	-.020	-.091	.018	.034	-.078	-.043	-.057	.140	.141	.013	.144	-.020	.364	1	.028	.043	.020	.118	.010	-.009	.012	.049	-.033	-.014	.007	-.020
16	Inverse Mills ratio	-.019	.015	-.076	.150	.066	-.046	.089	-.055	-.116	-.112	.068	-.167	.143	.004	.028	1	.075	.014	-.001	.152	.065	.066	.019	.101	-.065	-.143	-.498
17	Image colorfulness	.017	-.036	-.032	-.076	.131	-.024	.020	-.018	-.068	-.002	-.064	-.049	.049	.047	.043	.075	1	.191	.035	.086	.051	.022	.067	.102	-.041	.018	-.130
18	Image brightness	-.007	-.024	.034	-.071	.192	-.051	.021	-.021	-.055	.011	.002	.037	.016	.036	.020	.014	.191	1	.026	.058	.039	.032	.050	.068	-.019	-.067	-.088
19	Caption length	-.050	.005	-.109	-.059	-.050	-.061	.078	-.469	.462	.197	-.132	.363	.008	.056	.118	-.001	.035	.026	1	.378	.273	.179	.386	.142	.208	.057	.099
20	Caption exclamation marks	-.043	.014	-.008	-.030	-.021	-.021	.141	-.181	.016	-.020	-.027	.076	.042	.047	.010	.152	.086	.058	.378	1	.188	.083	.301	.203	.093	.035	-.129
21	Caption question marks	-.023	.029	-.025	.015	.046	.021	.087	-.191	-.020	.004	-.042	.053	-.006	.020	-.009	.065	.051	.039	.273	.188	1	.036	.155	.032	.013	.033	-.059
22	Caption hashtags	-.033	.017	-.001	-.048	-.001	-.037	.093	-.092	-.054	-.019	-.110	.077	.006	.023	.012	.066	.022	.032	.179	.083	.036	1	.109	.155	.004	-.034	-.083
23	Caption sentiment	-.039	.054	-.060	-.011	.024	.013	.189	-.251	.078	.047	-.026	.121	.043	.092	.049	.019	.067	.050	.386	.301	.155	.109	1	.201	.128	.038	-.039
24	Coupon	-.060	.078	.101	-.164	-.063	-.058	.287	-.045	-.200	-.089	.011	-.061	.137	.038	-.033	.101	.102	.068	.142	.203	.032	.155	.201	1	-.002	.015	-.197
25	Giveaway	-.001	.178	-.007	-.005	-.029	-.001	.015	-.070	.143	.004	.015	.074	-.022	-.005	-.014	-.065	-.041	-.019	.208	.093	.013	.004	.128	-.002	1	-.011	.098
26	Google trend endorsed brand	.002	.005	.041	.064	-.048	.050	.033	-.003	.076	.014	.052	.028	-.049	-.029	.007	-.143	.018	-.067	.057	.035	.033	-.034	.038	.015	-.011	1	.168
27	Number of prior endorsement posts	-.011	-.032	.018	-.091	-.102	.020	-.126	-.045	.320	.238	-.040	.249	-.140	-.049	-.020	-.498	-.130	-.088	.099	-.129	-.059	-.083	-.039	-.197	.098	.168	1

Table D2. Influencer engagement model – Variable descriptives

Variable	N	Mean	Std. Dev.	Min	Max
Post engagement	3,480	12,872.83	50,952.96	18	1,843,662
Product engagement	3,480	4.395	11.512	0	268
Visual salience	3,480	0	2.127	-4.601	11.031
Face	3,480	0.498	0.5	0	1
Visual complexity	3,480	3.656	0.518	1.129	5.044
Standardized disclosure	3,480	0.108	0.31	0	1
Textual disclosure	3,480	0.363	0.481	0	1
Brand link position	3,480	0.515	0.5	0	1
Number of links in caption	3,480	2.418	2.684	0	30
Number of links in image	3,480	4.766	5.778	0	20
Product-post integration	3,480	-0.811	0.083	-1.067	-0.321
Post-organic integration	3,480	-0.682	0.109	-0.935	-0.264
Recency	3,480	32.773	44.795	0.002	862.732
Abnormal prior post engagement	3,480	0.773	6.383	-73.464	47.766
Abnormal similar post engagement	3,480	0.066	1.229	-10.017	13.79
Inverse Mills ratio	3,480	1.859	0.41	0.123	3.119
Image colorfulness	3,480	37.65	17.153	0	149.044
Image brightness	3,480	152.868	34.939	26	245
Caption length	3,480	354.833	272.784	8	2,123
Caption exclamation marks	3,480	0.949	1.535	0	13
Caption question marks	3,480	0.278	0.648	0	7
Caption hashtags	3,480	0.844	3.193	0	30
Caption sentiment	3,480	0.562	0.408	-0.932	0.999
Coupon	3,480	0.393	0.488	0	1
Giveaway	3,480	0.022	0.145	0	1
Google trend endorsed brand	3,480	54.214	20.432	18	100
Number of prior endorsement posts	3,480	10.766	15.859	1	116

Web Appendix E: Algorithmic Targeting Model

To test whether recency, prior post engagement, and similar post engagement explain the reach of the post caused by algorithmic targeting, we collaborated with a brand in the entertainment industry with 129,000 followers (August 2022) and 6,710 posts created between July 2018 (starting date of the Instagram account) and August 2022. We gained access to a dataset that includes information on reach (i.e., number of users who saw the post). Note that we did not have this information in our watch and shoe samples. We only kept posts (n = 947) published between July 2018 and July 2019 to match the period where we observed the influencer posts. We modeled reach using a negative binomial regression model and controlled for the number of prior posts to account for a trend in reach over time (the results do not change if we exclude this variable from the model). We find that recency (.029, p < .001), prior post engagement (.042, p < .001), and similar post engagement (.058, p < .001) significantly explain a post's reach, as depicted in Table C1.

Table E1. Regression results for the algorithmic targeting model

	DV: Reach (number of users that were exposed to the post)	
(Intercept)	9.777***	(.074)
Recency	.029***	(.009)
Prior post engagement	.042***	(.010)
Similar post engagement	.058***	(.010)
Prior brand posts	.007	(.012)

Notes: *** p < .01; All variables are z-standardized; N = 947 brand posts. Standard error in parentheses.

Web Appendix F: Influencer Selection Model

Table F1. Results for the first-stage probit selection model

	DV: Selection of influencer	
(Intercept)	-1.477^{***}	(.208)
Number of similar influencers that endorse a product from the same category in the same week (log)	$.880^{***}$	(.027)
Influencer dummy	Yes	
Week dummy	Yes	

Notes: *** p < .01; N = 80,166. Standard error in parentheses.

Web Appendix G: Alternate Models for Influencer Engagement

Table G1. Nested and log-linear models

Model:	M1	M2	M3	M4	M5	M6
Description:	Only main variables	Control variables	Log-linear model	Only main variables	Control variables	Log-linear model
DV:	Post engagement	Post engagement	Post engagement	Product engagement	Product engagement	Product engagement
Visual salience	−.012 (.026)	−.043* (.025)	−.025** (.012)	.248*** (.031)	.224*** (.031)	.548*** (.084)
Face	.415*** (.049)	.542*** (.049)	.128*** (.024)	−.434*** (.060)	−.479*** (.061)	−.804*** (.169)
Visual complexity	−.019 (.024)	−.049** (.024)	.022** (.011)	−.085*** (.029)	−.096*** (.029)	−.253*** (.075)
Standardized disclosure	1.259*** (.075)	1.304*** (.074)	.089** (.039)	.530*** (.090)	.466*** (.089)	1.351*** (.267)
Textual disclosure	−.195*** (.049)	−.052 (.050)	.010 (.026)	.568*** (.060)	.419*** (.061)	.400** (.178)
Brand link position	.512*** (.050)	.139** (.055)	−.080*** (.023)	.169*** (.061)	.292*** (.068)	.674*** (.162)
Number of links in caption	.520*** (.056)	.598*** (.062)	.210*** (.033)	−.368*** (.071)	−.442*** (.080)	−.824*** (.230)
Number of links in image	−.382*** (.030)	−.444*** (.030)	.0004 (.018)	−.100*** (.037)	−.023 (.037)	−.126 (.125)
Product-post integration	−.208*** (.023)	−.143*** (.023)	.001 (.011)	.240*** (.028)	.219*** (.029)	.208*** (.075)
Post-organic integration	−.027 (.025)	.004 (.026)	.014 (.014)	−.038 (.031)	−.020 (.032)	−.107 (.096)
Recency		.027 (.023)	.048*** (.012)		.038 (.028)	.033 (.082)
Abnormal prior post engagement		.009 (.024)	.088*** (.010)		.086*** (.030)	.053 (.073)
Abnormal similar post engagement		−.078*** (.024)	.031*** (.011)		−.033 (.030)	−.100 (.076)
Inverse Mills ratio		−.280*** (.026)	.061*** (.021)		.041 (.033)	−.268* (.149)
Image colorfulness		.025 (.023)	.006 (.010)		−.002 (.058)	−.020 (.175)
Image brightness		.045** (.023)	.009 (.011)		−.052 (.054)	.159 (.146)
Caption length		−.290*** (.047)	−.035 (.025)		.397*** (.082)	.599*** (.200)
Caption exclamation marks		−.082* (.043)	−.006 (.021)		.041 (.046)	.011 (.216)
Caption question marks		−.103 (.067)	.022 (.029)		.025 (.032)	.027 (.077)
Caption hashtags		−.136*** (.037)	−.021 (.031)		.108 (.066)	.176 (.216)
Caption sentiment		.027 (.026)	.002 (.011)		1.379*** (.186)	−.214 (.438)
Coupon		−.263*** (.053)	−.007 (.031)		−.081*** (.029)	−.034 (.072)
Giveaway		.101 (.156)	.070 (.063)		.010 (.028)	.031 (.073)
Google trend endorsed brand		−.226*** (.060)	.231*** (.061)		.041 (.075)	−.238 (.423)
Number of prior endorsement posts		.007 (.028)	−.012 (.029)		−.027 (.035)	−.408** (.204)
Fixed effects (see Table 5)	No	No	Yes	No	No	Yes
Nagelkerke R²	.248	.315	.957	.140	.172	.502

Notes: ***p < .01, **p < .05; *p < .10. N = 3,480. Standard errors in parentheses.

Table G2. Alternate model specifications

Model:	M7	M8	M9	M10	M11	M12
Description:	Removed outliers for post engagement (< 5%/>95% quantile; n = 3132)		Interaction between Visual salience and face		Weighted by inverse of number of observations per brand	
DV:	Post engagement	Product engagement	Post engagement	Product engagement	Post engagement	Product engagement
Visual salience	−.006 (.009)	.358*** (.030)	−.035*** (.012)	.343*** (.035)	−.003 (.011)	.333*** (.031)
Face	.116*** (.018)	−.386*** (.061)	.124*** (.020)	−.362*** (.060)	.075*** (.023)	−.291*** (.066)
Visual complexity	.031*** (.008)	−.126*** (.028)	.022** (.009)	−.122*** (.027)	.011 (.009)	−.092*** (.027)
Standardized disclosure	.077*** (.028)	.626*** (.095)	.071** (.032)	.658*** (.093)	.012 (.034)	.721*** (.095)
Textual disclosure	.015 (.019)	.136** (.063)	.012 (.021)	.160*** (.062)	.051** (.024)	.207*** (.070)
Brand link position	−.046*** (.017)	.229*** (.058)	−.071*** (.019)	.215*** (.057)	−.037* (.021)	.284*** (.063)
Number of links in caption	.085*** (.025)	−.222** (.089)	.124*** (.027)	−.216** (.087)	.185*** (.029)	−.294*** (.092)
Number of links in image	.032** (.013)	−.109** (.047)	.019 (.015)	−.118** (.046)	−.009 (.015)	−.007 (.048)
Product-post integration	.006 (.008)	.222*** (.027)	−.011 (.009)	.180*** (.026)	−.013 (.008)	.202*** (.024)
Post-organic integration	.027*** (.010)	−.033 (.035)	.024** (.011)	−.050 (.034)	−.006 (.013)	−.049 (.037)
Recency	.034*** (.009)	.023 (.031)	.039*** (.010)	.017 (.030)	.075*** (.012)	−.023 (.038)
Abnormal prior post engagement	.068*** (.008)	.080*** (.027)	.075*** (.009)	.030 (.026)	.068*** (.008)	.001 (.025)
Abnormal similar post engagement	.005 (.008)	−.094*** (.029)	.026*** (.009)	−.031 (.028)	.036*** (.009)	−.028 (.026)
Inverse Mills ratio	.046*** (.016)	−.192*** (.050)	.041** (.018)	−.195*** (.050)	.019 (.021)	−.147** (.057)
Image colorfulness	.007 (.008)	−.029 (.027)	−.001 (.008)	−.037 (.026)	.008 (.009)	.018 (.027)
Image brightness	−.002 (.008)	.023 (.026)	.002 (.009)	.009 (.026)	−.007 (.009)	−.047* (.026)
Caption length	−.024 (.019)	−.005 (.067)	−.063*** (.021)	−.023 (.065)	−.067*** (.021)	−.085 (.067)
Caption exclamation marks	.001 (.016)	−.053 (.054)	−.001 (.017)	−.043 (.053)	−.018 (.019)	−.159*** (.058)
Caption question marks	−.009 (.022)	.203*** (.072)	.037 (.024)	.334*** (.069)	.075*** (.026)	.428*** (.075)
Caption hashtags	−.001 (.023)	.046 (.079)	−.007 (.025)	−.002 (.076)	−.039 (.031)	.105 (.087)
Caption sentiment	.002 (.008)	.036 (.029)	.001 (.009)	.032 (.028)	.009 (.010)	.035 (.030)
Coupon	−.020 (.023)	.067 (.080)	−.016 (.026)	.017 (.077)	−.014 (.032)	.058 (.096)
Giveaway	.151*** (.047)	.849*** (.154)	.142*** (.052)	.857*** (.149)	.045 (.062)	.890*** (.169)
Google trend endorsed brand	.065 (.046)	.185 (.158)	.085* (.050)	.327** (.152)	.014 (.045)	.205 (.132)
Number of prior endorsement posts	−.037* (.022)	−.185** (.075)	−.034 (.024)	−.155** (.072)	−.098*** (.027)	−.331*** (.079)
Visual salience x Face			.041* (.021)	−.046 (.065)		
Nagelkerke R²	.948	.632	.963	.623	.963	.675

Notes: ***$p < .01$, **$p < .05$; *$p < .10$. N = 3,480. Standard errors in parentheses.

Web Appendix H: Instrumental Variables Model

Table H1. Results for first-stage models with instrumental variables

Dependent variable:	Aggregate post engagement		Aggregate product engagement	
Average log(likes) of non-endorsement posts	1.072***	(.005)	−.675***	(.015)
Average log(comments) of non-endorsement posts	−.060***	(.006)	1.530***	(.020)
Nagelkerke R^2	.983		.827	
Nagelkerke R^2 without instrumental variables	.633		.700	

Notes: *** $p < .001$. The models include all variables later used in the second-stage model. N = 17,444. Standard errors in parentheses.

Table I1. Brand engagement model – Variable correlations

No.	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	Brand engagement		.09	.40	-.07	.00	.02	.07	.05	.21	.04	-.05	-.02	-.08	-.50	-.05	-.04	-.20	.04	-.07	-.02	-.03	.36	-.07
2	Aggregate post engagement	.09		.44	.07	-.08	-.07	-.01	-.08	.28	.01	.07	.02	-.05	.03	.08	.05	-.02	.04	.09	.00	.00	.05	.01
3	Aggregate product engagement	.40	.44		.04	.90	-.04	.22	.01	.33	-.05	.05	.02	-.06	.04	.22	.05	-.05	.10	.06	.06	-.01	.29	.20
4	$\hat{\varphi}^{post\ engagement}$	-.07	.07	.04		.00	-.01	-.01	.00	.03	.00	.00	.00	.00	-.03	.00	.00	.00	.00	.01	.00	.00	.04	.01
5	$\hat{\varphi}^{product\ engagement}$	.00	-.08	.90	.00		-.02	.07	.00	.04	.00	.00	.00	.00	.00	-.01	.00	-.03	.00	.00	.00	.00	.05	.01
6	Recency	.02	-.07	-.04	-.01	-.02		.05	.08	.00	.03	-.03	-.05	-.03	-.30	-.07	-.04	-.50	-.03	-.08	.00	.00	.68	-.95
7	Abnormal prior post engagement	.07	-.01	.22	-.01	.07	.05		.10	-.01	-.03	-.06	-.03	.00	-.90	-.03	-.02	-.94	-.02	-.08	.01	.07	.21	-.50
8	Abnormal similar post engagement	.05	-.08	.01	.00	.00	.08	.10		.01	.00	-.02	.01	.00	.05	.00	-.01	-.06	.07	.06	-.01	.24	.04	.05
9	Average Inverse Mills ratio	.21	.28	.33	.03	.04	.00	-.01	.01		.04	.06	.04	-.06	-.03	.04	.03	-.57	.08	.05	-.07	-.04	.05	.04
10	Image colorfulness	.04	.01	-.05	.00	.00	.03	-.03	.00	.04		.83	.06	.00	.07	.05	-.02	.01	-.02	.03	.01	-.01	.06	-.04
11	Image brightness	-.05	.07	.05	.00	.00	-.03	-.06	-.02	.06	.83		.28	-.09	.00	.04	.05	.10	.00	.26	-.02	.00	-.08	.08
12	Face	-.02	.02	.02	.00	.00	-.05	-.03	.01	.04	.06	.28		.06	.09	.05	.05	.09	.04	.00	-.01	-.01	-.05	.05
13	Visual complexity	-.08	-.05	-.06	.00	.00	-.03	.00	.00	-.06	.00	-.09	.06		.04	-.03	.00	.04	-.01	.04	.00	.04	-.04	.01
14	Caption length	-.50	.03	.04	-.03	.00	-.30	-.90	.05	-.03	.07	.00	.09	.04		.49	.50	.56	.27	.57	.07	.38	-.27	.96
15	Caption exclamation marks	-.05	.08	.22	.00	-.01	-.07	-.03	.00	.04	.05	.04	.05	-.03	.49		.25	.93	.40	.37	.08	.36	-.01	.20
16	Caption question marks	-.04	.05	.05	.00	.00	-.04	-.02	-.01	.03	-.02	.05	.05	.00	.50	.25		.90	-.03	.07	-.01	.03	-.04	.07
17	Caption hashtags	-.20	-.02	-.05	.00	-.03	-.50	-.94	-.06	-.57	.01	.10	.09	.04	.56	.93	.90		-.01	.36	.05	.00	-.82	.28
18	Number of links in caption	.04	.04	.10	.00	.00	-.03	-.02	.07	.08	-.02	.00	.04	-.01	.27	.40	-.03	-.01		.05	-.02	.24	.06	.05
19	Caption sentiment	-.07	.09	.06	.01	.00	-.08	-.08	.06	.05	.03	.26	.00	.04	.57	.37	.07	.36	.05		.02	.66	-.09	.67
20	Coupon	-.02	.00	.06	.00	.00	.00	.01	-.01	-.07	.01	-.02	-.01	.00	.07	.08	-.01	.05	-.02	.02		.00	.04	-.01
21	Giveaway	-.03	.00	-.01	.00	.00	.00	.07	.24	-.04	-.01	.00	-.01	.04	.38	.36	.03	.00	.24	.66	.00		.05	-.03
22	Number of prior brand posts	.36	.05	.29	.04	.05	.68	.21	.04	.05	.06	-.08	-.05	-.04	-.27	-.01	-.04	-.82	.06	-.09	.04	.05		-.36
23	Google trend Brand	-.07	.01	.20	.01	.01	-.95	-.50	.05	.04	-.04	.08	.05	.01	.96	.20	.07	.28	.05	.67	-.01	-.03	-.36	

Table I2. Brand engagement model – Variable descriptives

Variable	N	Mean	Std. Dev.	Min	Max
Brand engagement	17,444	25,364.53	38,810.31	330	590,351
Aggregate post engagement	17,444	31,784.90	79,038.95	0	1,938,903
Aggregate product engagement	17,444	12.839	31.076	0	278
$\widehat{\varphi}^{\text{post engagement}}$	17,444	-0.01	0.928	-3.079	6.022
$\widehat{\varphi}^{\text{product engagement}}$	17,444	-0.026	1.076	-1.36	6.558
Recency	17,444	18.234	26.547	0.017	1,965.42
Abnormal prior post engagement	17,444	-0.436	3.97	-16.093	15.229
Abnormal similar post engagement	17,444	-0.029	2.113	-19.506	18.796
Average Inverse Mills ratio	17,444	1.146	0.945	0	2.995
Image colorfulness	17,444	37.087	19.295	0	149.44
Image brightness	17,444	152.412	40.309	6	255
Face	17,444	3.612	0.603	0	5.301
Visual complexity	17,444	0.266	0.442	0	1
Caption length	17,444	143.1	95.436	3	1,312
Caption exclamation marks	17,444	0.323	0.643	0	10
Caption question marks	17,444	0.131	0.355	0	3
Caption hashtags	17,444	2.771	4.54	0	28
Number of links in caption	17,444	0.742	0.815	0	34
Caption sentiment	17,444	0.398	0.393	-0.966	0.998
Coupon	17,444	0.006	0.078	0	1
Giveaway	17,444	0.015	0.122	0	1
Number of prior brand posts	17,444	753.833	570.654	1	2,414
Google trend Brand	17,444	46.525	19.318	17	100

Web Appendix J: Alternate Models for Brand Engagement

Table I1. Alternate brand engagement models

	Only main variables	Control variables	OLS with log-transformed dependent variable
Constant	8.221*** (.031)	2.809*** (.113)	7.705*** (.142)
Endorsement post engagement			
Aggregate post engagement	.181*** (.004)	.115*** (.004)	.017*** (.003)
Aggregate product engagement	.036*** (.007)	.117*** (.007)	.046*** (.007)
Control functions			
$\widehat{\varphi}^{Sender}$		−.074*** (.007)	−.007 (.004)
$\widehat{\varphi}^{Product}$		−.050*** (.007)	−.020*** (.005)
Algorithmic targeting			
Recency		−.025*** (.007)	.002 (.004)
Abnormal prior post engagement		−.039*** (.007)	.049*** (.005)
Abnormal similar post engagement		.043*** (.007)	.065*** (.004)
Influencer selection			
Average Inverse Mills ratio		.026*** (.009)	−.030*** (.005)
Control variables			
Image colorfulness		.045*** (.007)	.0004 (.004)
Image brightness		−.090*** (.007)	−.008* (.004)
Face		.014** (.007)	.003 (.004)
Visual complexity		−.112*** (.017)	−.041*** (.011)
Caption length		.348*** (.015)	−.054*** (.010)
Caption exclamation marks		−.058*** (.022)	.006 (.014)
Caption question marks		−.069** (.028)	.077*** (.017)
Caption hashtags		−.580*** (.011)	−.066*** (.010)
Number of links in caption		−.199*** (.018)	−.050*** (.012)
Caption sentiment		−.073*** (.008)	.025*** (.005)
Coupon		−.204** (.085)	.019 (.051)
Giveaway		−.286*** (.059)	.619*** (.037)
Google trend Brand		1.031*** (.018)	.425*** (.018)
Number of prior brand posts		.132*** (.007)	−.068*** (.020)
Fixed effects (see Table 8)	No	No	Yes
Nagelkerke R²	.202	.488	.862

Notes: ***p < .01, **p < .05; *p<.10. N = 17,444. Standard errors in parentheses.