WHEN DO INFLUENCER ENDORSEMENT POSTS DRIVE BRAND ENGAGEMENT? AN EMPIRICAL INVESTIGATION ON INSTAGRAM

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Keywords

Social media, Influencer marketing effectiveness, Consumer engagement, Brand engagement, Visual attention

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Abstract

While recent research has studied drivers of audience engagement with influencer endorsement posts, no research shows how these posts drive engagement with the endorsed brand. We empirically investigate which influencer endorsement posts drive brand engagement on Instagram. Our empirical analysis relies on a sample of Instagram posts made by brands and influencers endorsing those brands. Brand engagement is measured as the number of likes and comments for a brand's own posts. In the case of influencer endorsement posts we distinguish between sender- and product-directed engagement. The former is measured as the number of likes and comments not referring to the product endorsed by an influencer, the latter is measured as the number of comments referring to the endorsed product. We find that greater sender- and product-directed engagement explain increases in brand engagement. However, the effect of product-directed engagement is about four times larger. We then study several textual and visual cues that we predict to stimulate attention to the endorsed product. Most of these cues have opposing effects on sender- and product-directed engagement such that designing endorsement posts with the goal of increasing sender-directed engagement is expected to lower product-directed engagement and thus not drive brand engagement effectively.

Keywords

Social media, Influencer marketing effectiveness, Consumer engagement, Brand engagement, Visual attention

Social media-based influencer marketing has become a key component of digital marketing strategies (Hughes, Swaminathan, and Brooks 2019; Leung, Gu, and Palmatier 2022a) and is one of the most pressing research topics in social media marketing (Appel et al. 2019; Moorman et al. 2019; Leung et al. 2022a). The influencer marketing industry is expected to grow to $16.4 billion in 2022, following an average 37% yearly increase in the last three years (Influencer Marketing Hub 2022). Influencers endorse brands in their posts to their followers by visually presenting and providing information about the brands' products. For followers, these endorsement posts might generate awareness, interest, and positive attitudes towards the endorsed brand that can turn into increased engagement with the endorsed brand (Leung et al. 2022a). But which influencer posts lead to brand engagement, and which do not?

Prior academic research in the domain of influencer marketing has not yet answered this question sufficiently. While several studies investigate how influencer (Valsesia et al. 2020), post (Hughes et al. 2019), and follower (Leung et al. 2022b) characteristics drive sender-directed engagement with the influencers' endorsement posts (e.g., the number of likes and comments of endorsement posts), it is not clear if this engagement also creates down-stream consequences such as brand engagement (e.g., the number of likes and comments for brand posts; Lee, Hosanagar, and Nair 2018) or even sales.

Yet, understanding how influencer posts drive brand engagement is important for two main reasons. First, according to recent research, increasing brand engagement on social media can be considered an important marketing goal. For example, Xie and Lee (2015) show that exposure to brand posts increases consumers' likelihood to purchase the brands' products. Kumar et al. (2016) and Colicev et al. (2018) find that the volume of engagement with brand posts explains brand awareness, sales, and shareholder value. Similarly, Rishika et al. (2013) and Mochon et al. (2017) show that when individuals follow a brand page on social media, it results in higher levels of in-store purchases. A recent meta-analysis by Liadeli et al. (2022) shows that a brand's owned social media content drives sales with an average elasticity of .353, thus it is key for marketers to understand how brands can direct consumers to their owned content on social media. Second, two industry reports released in 2022 show that raising brand engagement is practitioners' top goal for influencer marketing, even being listed slightly above directly increasing sales (Influencer Marketing Hub 2022; Meltwater 2022). Third, influencer posts that drive sender-directed engagement might not drive brand engagement. Prior research indicates that individuals are more likely to interact with digital content if the brand associated with it is less salient (Akpinar & Berger, 2017; Hartmann et al. 2019). This finding implies that influencer posts with low brand saliency may receive more sender-directed engagement but may not necessarily lead to an increase in brand engagement.

To study the proposed effects, we collected 3,480 endorsement posts from 555 influencers endorsing 15 brands from two product categories (watches and shoes) as well as 17,444 brand posts from Instagram posted between February 2017 and July 2019. We then test if engagement with influencer endorsement posts has an effect on *brand engagement,* measured as the number of likes and comments brand posts receive. We differentiate two forms of engagement with influencer posts: *Sender-directed engagement*, measured as the mere number of likes and comments not referring to the endorsed product the influencer post receives, and *product-directed engagement*, measured as the number of comments referring to endorsed product (e.g., "I like those shoes!" in a post endorsing Nike shoes; see Hartmann et al. 2021 for a similar metric). In the next step, we investigate how visual and textual drivers of attention towards the endorsed product are related to sender- and product-directed engagement. We accounted for several sources of endogeneity, such as the influencer selection process, algorithmic targeting of posts, and different sources of unobserved heterogeneity, by using instrumental variables and fixed effects for influencers, brands, and time periods.

Our research makes several theoretical and managerial contributions to extant literature on influencer marketing. As mentioned, recent studies mostly investigated drivers of sender-directed engagement with influencer endorsement posts, but most of them do not account for downstream consequences of such engagement. In line with Leung et al. (2022b, p. 38) arguing 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", we question how engagement for influencer endorsement posts is related to brand engagement (i.e., engagement with brand owned content). Our empirical results show that both endorsement posts with high sender-directed engagement and product-directed engagement explain an increase in brand engagement, but that the effect of product-directed engagement is about four times stronger.

Second, we find that several decisions concerning the design of the endorsement post have opposing effects on sender- and product-directed engagement. For example, posts in which the influencer's face is visible and those with lower visual product saliency (e.g., small depiction size) gain more sender-directed engagement but also less product-directed engagement. Likewise, textual cues that drive attention to the product (e.g., mentioning the brand at the beginning of the caption text) increase product-directed engagement but decrease sender-directed engagement. Interestingly, sponsorship disclosure has a positive effect on both sender- and product-directed engagement. These findings indicate that creating sender- and product-directed engagement are conflicting objectives when influencers design endorsement posts. As sender-directed engagement is a popular performance metric for selecting, evaluating and compensating influencers (Influencer Marketing Hub 2022), current practice might miss potential uplifts in brand engagement through a post design that focuses too narrowly on sender-directed engagement. While creating sender-directed engagement is an important goal on its own, managers aiming at building brand engagement should be aware of this misalignment.

Third, our research contributes to the literature on performance metrics for evaluating the effectiveness of influencer marketing (Leung et al. 2022b). Our findings indicate that influencer posts with high levels of product-directed engagement induce higher levels of brand engagement. We propose a straightforward measure to access product-engagement from publicly available social media data by counting the number of comments referencing the endorsed product or brand. This measure is of potential interest both for managers and researchers. While managers could potentially measure downstream consequences resulting from endorsement posts by tracking sales through referral links and coupons, they can only do so for their products. Hence, this limits their ability to learn about the effectiveness of different design and influencer choices from posts sponsored by other brands. Furthermore, industry reports show that driving brand engagement is a distinct yet not less important goal for influencer marketing compared to driving sales. Therefore, managers could additionally use product-engagement to access an endorsement post's ability to generate brand engagement. This measure might especially be interesting to evaluate and select new influencers, as their ability to drive sales is not observable for companies before cooperation. For researchers, sales data is not directly available, especially for a larger sample of companies and influencers. While this might partially explain recent research's focus on sender-directed engagement as the outcome variable of interest, using product-directed engagement as an alternative measure of effectiveness seems valuable given our evidence that product-directed engagement is stronger related to brand engagement.

Fourth, our paper contributes to the literature on visual social media communication (Lie & Xie 2020; Hartmann et al. 2021) by investigating how the visual design of an endorsement post drives engagement with the post and the endorsed product We investigate three facets of the visual design: How to present the product (size, position, brightness), how to present the influencer (absence vs. presence), and how to choose the background in terms of visual complexity. As social media have moved from text to images (or videos), these findings are important for influencers and managers considering how the visual design for influencer posts drives engagement.

Related Literature

Table 1 summarizes recent studies situated in the domain of brand endorsement posts on social media, both for influencers and consumers (i.e., word of mouth). Prior research has investigated the drivers of sender-directed engagement using data from social media platforms (e.g., Instagram and Weibo) or online blogs (Hughes, Swaminathan, and Brooks 2019). The operationalization of sender-directed engagement differs. For example, Hughes, Swaminathan, and Brooks (2019), Valsesia, Proserpio, and Nunes (2020), Karagür et al. (2022), and Alibakhshi and Srivastava (2022) count the number of likes of social media posts on different platforms, while Valsesia, Proserpio, and Nunes (2020) and Leung et al. (2022b) also consider reposts on Twitter and Weibo. Only two studies investigate outcome measures that are conceptually related to our definition of product-directed engagement: First, Hartmann et al. (2021) count the number of comments classified as purchase intentions on consumer-generated posts that contain a brand logo. Their research is situated in the domain of unpaid brand-related social media posts where senders are not incentivized and firms have no control over posted content. In addition, they do not test whether their operationalization of purchase intention is linked to actual purchase or engagement for the endorsed brand. Second, Wies, Bleier, and Edeling (2022) model the relationship between number of followers and story engagement. In contrast to posts, stories allow the influencer to add a link that leads the user directly to the homepage of the endorsed product. As can be seen in Table 1, none of the prior studies on influencer marketing investigates whether the engagement generated by endorsement posts also increases engagement for the endorsed brand (i.e., brand engagement).

On the explanatory side, several authors have studied characteristics of the influencer, such as expertise (Hughes, Swaminathan, and Brooks 2019), number of followers (Wies et al. 2022), number of followees (i.e., the number of accounts the influencer is following; Valsesia, Proserpio, and Nunes 2020), characteristics of the followers, such as follower–brand fit (Leung et al. 2022b), and changes in the platform, such as the introduction of the story-feature on Instagram (Alibakhshi and Srivastava 2022).

Table 1. Empirical studies on endorsement post engagement

Authors	Platform	Influencer (vs. consumer)	Dependent variables (Engagement)			Explanatory variables
			Sender-directed	Product-directed	Brand	
Hughes, Swaminathan, and Brooks 2019	Blog, Facebook	✓	✓			Campaign type; Expertise; Hedonic value; Campaign incentive
Li and Xie 2020	Twitter, Instagram		✓			Inclusion of a face
Valsesia, Proserpio, and Nunes 2020	Twitter	✓	✓			Number of followees
Karagür et al. 2022	Instagram	✓	✓			Sponsorship disclosure
Hartmann et al. 2021	Twitter, Instagram		✓	✓		Three forms of selfies (consumer, brand, packshot)
Leung et al. 2022b	Weibo	✓	✓			Seven influencer, follower, and pot characteristics
Alibakhshi and Srivastava 2022	Instagram	✓	✓			Introduction of the story feature
Cheng et al. 2022	Bilibili	✓	✓			Authenticity; Sponsorship disclosure
Wies, Bleier, and Edeling 2022	Instagram	✓	✓	✓		Number of followers
Cascio Rizzo et al. 2023	Instagram, TikTok	✓	✓			Sensory language
Chung, Ding, and Kalra 2023	Instagram	✓	✓			Post reference to close social ties
This study	**Instagram**	✓	✓	✓	✓	**Textual and visual drivers of product attention**

Regarding the content of the endorsement posts, most studies focusing on influencers investigate textual features of the post. For example, Hughes, Swaminathan, and Brooks (2019) extracted the functional and hedonic value of the blog post, and Leung et al. (2022b) study the positivity of a post’s text. Karagür et al. (2022) and Leung et al. (2022b) extract the sponsorship disclosure statement (e.g., “#ad”) from text or contextual information (e.g., standardized disclosure badge), while Cheng et al. (2022) manually label influencer videos regarding the degree of disclosure clarity. Cascio Rizzo et al. (2023) show that sensory language increases sender-directed engagement. Our work extends prior research in the domain of influencer marketing by studying textual drivers of product attention that have previously not been studied, such as whether the endorsed brand is mentioned at the beginning or the end of the caption text.

In addition to textual features of the post, authors have started to study visual properties of social media posts from image-based platforms such as Instagram. The study by Li and Xie (2020) investigates whether consumer-generated posts linked to a brand generate more engagement when they contain an image or when there is a face on the image. Further, Hartmann et al. (2021) compare several types of selfies and find that consumer selfies (i.e., images showing the face) received more post but less product-directed engagement. Similarly, Cascio Rizzo et al. (2023) control for the presence of a face as well as the facial expression, but do not find an effect on sender-directed engagement. Our work extends prior research in the domain of influencer marketing by studying visual drivers of product attention that have previously not been studied, such as the size, centrality, and brightness of the endorsed product shown in the image post. To the best of our knowledge, none of the previous studies has investigated the visual characteristics of the endorsed product.

Theoretical Background

Driving Brand Engagement through Influencer Marketing

In the literature, customer engagement is defined as an activity of the customer (behavioral manifestation) towards a brand or firm (Van Doorn et al. 2010; Kumar et al. 2016). The frequently referred-to definition proposed by Hollebeek, Glynn, and Brodie (2014) describes consumer brand engagement “as a consumer’s positively valenced brand-related cognitive, emotional and behavioral activity during or related to focal consumer/ brand interactions” (p. 149). In the social media context, customer engagement has been used with a similar conceptual scope, as researchers have emphasized that it refers to interactions between consumers and brands on social media (Lee, Hosanagar, and Nair 2018). Focusing on brand engagement seems all the more relevant as prior research showed that social media brand engagement has predictive power regarding firm performance (Rishika et al. 2013; Kumar et al. 2016) and, thus, can be used to evaluate the effectiveness of a firm's social media marketing activities.

Within a social network such as Instagram, brands can reach consumers in three ways. First, a brand's post can appear in a user's explore page feed. The explore page shows content from accounts a user does not follow to and thus allows a user to explore new content, both from personal and firm accounts. A recommender system algorithm sorts the explore page to highlight content that users are more likely to engage with. Second, brands can launch targeted ads that appear next to organic content, either in the explore page feed or on the feed of accounts a user is already following. Third, brands can be linked in a post such that users who see the post might recognize the linked brand. Typically, brands are linked in posts if branded products are part of the content, such as users linking a fashion brand when presenting their new outfit. Influencer marketing describes the practice of brands that compensate users (i.e., influencers) to endorse and link the brand account within the organic posts of the user. If followers of the influencer recognize the endorsed brand, the endorsement post might first generate awareness and consideration of the endorsed product. Next, consumers might decide to learn more about the brand and the endorsed product by following the link to the account of the endorsed brand and engage with brand owned posts. The assumed effectiveness of Influencer marketing relies on the notion that influencers establish close relationships with their followers, leading to trust and authenticity that makes them persuasive sources for brands (Waltenrath et al., 2022). A Nielsen study shows that consumers are more than twice as likely to trust an influencer's endorsement post compared to brand ads on social media (Nielsen, 2021).

Engagement with Influencer Posts

For influencers, the creation of engagement with their posts is their raison d'être. Influencers by definition are creators of engaging content that followers approve of, which is evidenced through likes and comments (Sherman et al., 2016). Moreover, creating engaging content allows influencers to increase their potential reach within a social network (Lipsman et al., 2012) as social media algorithms will forward engaging content to potential new followers. However, when endorsing brands, influencers risk losing followers who most often might be particularly interested in non-sponsored content shared by influencers. A recent study by Cheng and Zhang (2023) supports this idea as the authors found that influencers lost 0.17% of followers when posting a sponsored video compared to an organic video. Based on the persuasion knowledge model (Friestad and Wright 1994), it can be argued that factors that lead to the realization that a post is an attempt to persuade followers to engage with the endorsed product will activate persuasion knowledge and increase followers' reactance to engage with the endorsement post. Expecting that followers value influencers' intrinsic motivations and noncommercial orientation (Audrezet et al. 2018), influencers might refrain from making the commercial orientation of their endorsement posts too obvious and might rather be interested in making the endorsement post look like organic content (Cheng & Zhang 2023).

While brands pay influencers to endorse their products, they typically do not control the creative content creation process given the influencers profound knowledge of their audiences' preference and perception of authenticity (Cascio Rizzo et al., 2023). However, brands indirectly control this process by setting performance metrics that they perceive as relevant to select and evaluate the performance of influencer. Influencers are aware of these performance metrics and are likely to create content that is in line with brands' performance metrics in order to negotiate a higher compensation for their current and future endorsement posts. According to a recent survey (Influencer Marketing Hub 2022), managers widely consider sender-directed engagement with the influencer post (e.g., number of clicks, likes and comments) as the most important performance metric. Taken together, influencers are incentivized to create content that generates high levels of sender-directed engagement while knowing that endorsements posts with a strong commercial orientation will potentially reduce engagement (Cheng & Zhang 2023).

Relationship between Sender- and Product-directed Engagement and Brand Engagement

For brands aiming at increasing brand engagement through influencer marketing, focusing on sender-directed engagement as a key performance metric might be advisable as long as more engagement with the endorsement post leads to more brand engagement. While practitioners and, to a lesser extent, academic research use the term “engagement” to summarize different types of interactions with influencer posts such as liking, commenting, clicking and sharing, we argue in line with Leung et al. (2022b) that “not every form of engagement is created equal” (p.112) and differentiate between engagement that is directed at the sender (i.e., sender-directed engagement; measured through counting the number of likes and comments not referring to the endorsed product) and engagement that is directed at the endorsed product (i.e., product-directed engagement; measured through counting the number of comments referring to the endorsed product). To generate sender-directed engagement, followers must interact with the endorsement posts, and it is therefore plausible to assume that they elaborated on the content of the post to a certain extent. While this elaboration might or might not include paying attention to the endorsed product, it is straightforward to predict that endorsements posts with a high number of sender-directed engagement also lead to higher brand engagement as each interacting follower was exposed to the endorsed product. In contrast, as product-directed engagement requires the follower to mention the endorsed product or brand in a comment (e.g., “I like the watch you are wearing!”), the follower must have paid attention to the endorsed product and elaborated on the endorsement. If the comment has a positive sentiment, we can further conclude that the follower likes the endorsed product, which corresponds to a more advanced stage in the consumer decision journey. Thus, product-directed engagement is more likely to transfer into brand engagement. Hence, we predict that both sender- and product-directed engagement will drive brand engagement, but that the effect of product-directed engagement should be stronger.

Drivers of Sender- and Product-directed Engagement in Influencer Endorsement Posts

Assuming that sender- and product-directed engagement drive brand engagement to a varying extent, it is of high importance to understand when endorsement posts create high levels of sender- or product-directed engagement. To engage for the endorsed product, it is necessary that users first pay attention to the endorsed product. In what follows, we review the theoretical and empirical literature on attention processes in marketing to explain how visual and textual elements of Instagram endorsement posts drive attention to the endorsed product.

Instagram is a social media platform where visual information is central. In the following, we investigate three facets of the visual design: How visually salient a product is in a posted image, whether the influencer's face is visible, and how visually complex the posted image is.

Product saliency comprises three visual factors about the product in a post: size, brightness, and position/centrality. Making a product larger or brighter or presenting it more centrally in an image will direct followers' attention to the endorsed product. Chandon et al. (2009), for example, tested the effect of surface size by varying the number of shelf facings. The authors showed that brands with a larger number of facings attracted more attention and were chosen more often. Atalay, Bodur, and Rasolofoarison (2012) showed an effect of centrality on attention and choice. Testing the effect of brightness, Milosavljevic et al. (2012) provided evidence that more salient product alternatives received more attention and were more likely to be chosen.

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 (Cummins, Gong, and Reichert 2021). Sullivan et al. (2017), for example, found that visual elements in television ads distract consumers from paying attention to risk information when presented simultaneously. Hartmann et al. (2021) showed that face presence led to fewer statements of purchase intention in the comments.

Visual complexity is a visual feature that is supposed to influence product attention. Complex post images consist of several visual elements that all compete for followers' attention. Rosenholtz, Li, and Nakano (2007) provided evidence that visual complexity affects performance (in terms of response times) when humans are given simple search tasks. Visschers, Hess, and Siegrest (2010) found that respondents paid 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 products simply because there are fewer objects competing for followers' attention.

There is a lack of research testing the effects that visual features of an image might have on sender-directed engagement. Two studies, however, tested the effect of the presence of a face on sender-directed engagement. Li and Xie (2020) found that face presence increased sender-directed engagement on Twitter (though not on Instagram, which is more focused on media sharing, such as pictures and videos). Moreover, Hartmann et al. (2021) showed that face presence on consumers' brand-directed posts led to increased sender-directed engagement on both platforms and fewer statements of purchase intention by followers in related comments. While neither study is situated in the influencer context, these first results regarding face presence suggest that attention towards the face of an influencer and away from a product will increase sender-directed engagement and decrease product-directed engagement.

Besides visual features, Instagram posts comprise textual information that drives product attention. A brand link in an influencer post (i.e., a link to the account of the brand that paid the influencer for the endorsement) helps social media users recognize that the post endorses a product of the respective brand and thus also serves as an informational prime. The attention paid to this cue could depend on the position within the caption as well as the number of cues competing for attention (i.e., other linked accounts).

Additionally, sponsorship disclosures are a post characteristic that stresses the promotional context of a post. In most countries, it is mandatory for influencers to add partnership disclosures to their posts if they receive financial compensation for promoting products or brands. The partnership disclosure statement can be included in the form of a badge above the posted image (standardized disclosure; Karagür et al. 2022). In other posts, a disclosure might be included in the text, for example, as #ad or #sponsored. Previous research has shown that partnership disclosures can function as an informational prime (Boerman 2020) that changes how users process a post. Guo et al. (2018) investigated the effectiveness of disclosures using eye-tracking in the context of product placements. The authors showed that a disclosure statement increased the attention paid to the product, which, in turn, increased awareness of the persuasion attempt, brand recognition, and brand attitude. The aforementioned empirical studies suggest disclosure has a negative effect on sender-directed engagement in line with the activation of persuasion knowledge. However, consumers might evaluate persuasion attempts as fairer and less manipulative in posts that include disclosures; thus, including disclosures could also lead to increased sender-directed engagement. Recent field studies come to different conclusions. While Karagür et al. (2022) found a negative effect of disclosure on sender-directed engagement, Chen, Yan, and Smith (2022) found a positive effect. The studies differ regarding the social network considered as well as the country of investigation. Regarding the empirical setting (Instagram posts in western countries), our setting is similar to that considered by Karagür et al. (2022). Therefore, we expect to find that sponsorship disclosure has a negative effect on sender-directed engagement.

While drivers of product attention should evoke more product-related thoughts and thus also increase product-directed engagement, the effect on sender-directed engagement is less clearly predictable. Based on the persuasion knowledge model (Friestad and Wright 1994), it can be argued that factors that lead to the realization that a post is an attempt to persuade followers to engage with the endorsed product will activate persuasion knowledge. This theory is in line with Cheng and Zhang's (2023) finding that influencers loose followers when posting sponsored compared to organic content. Consequently, textual and visual factors that positively influence attention allocation to the endorsed product might have negative effects on sender-directed engagement. We therefore hypothesize that drivers of product attention will have opposing effects on sender-directed and product-directed engagement.

Empirical Setting

The empirical setting considers influencer Instagram posts endorsing brands as well as posts created by these brands using their own accounts. We focus on studying how users interact with these posts. The behavioral process underlying our observations can be described as follows: users observe influencer posts where a particular branded product is endorsed. Users might pay attention to the endorsed product and become interested, which we cannot observe. However, we can observe whether users interact with the post by liking or commenting it (sender-directed engagement) or writing a comment referring to the product (e.g., "the watch looks great!"; product-directed engagement). In the next step, users might want to learn more about the brand and visit its Instagram account. While we cannot observe whether a specific user visits the account of the brand, at the aggregate level we can observe how many users interact with the posts of the brand by liking or commenting them (brand engagement). The *brand engagement model* thus seeks to explain increases in brand engagement as a function of sender- and product-directed engagement of influencer posts endorsing the respective brand. The model will help us to determine which influencer endorsement posts (i.e., those with high sender-directed engagement vs. those with high product-directed engagement) lead to greater brand engagement. As brands are endorsed by multiple influencers at the same time, we aggregate sender- and product-directed engagement on a brand level (i.e., count the number of likes, comments, and product-related comments for all influencers posts endorsing a particular brand). Next, we aim to understand which endorsement posts generate higher levels of sender- vs. product-directed engagement. Therefore, the *influencer engagement model* seeks to explain increases in sender- and product-directed engagement as a function of visual (e.g., visual product saliency) and textual (e.g., standardized disclosure) endorsement posts characteristics that are theoretically expected to drive the attention paid to the endorsed product. We hypothesize that these drivers of product attention have opposing effects on sender- and product-directed engagement. The conceptual framework is presented in Figure 1.

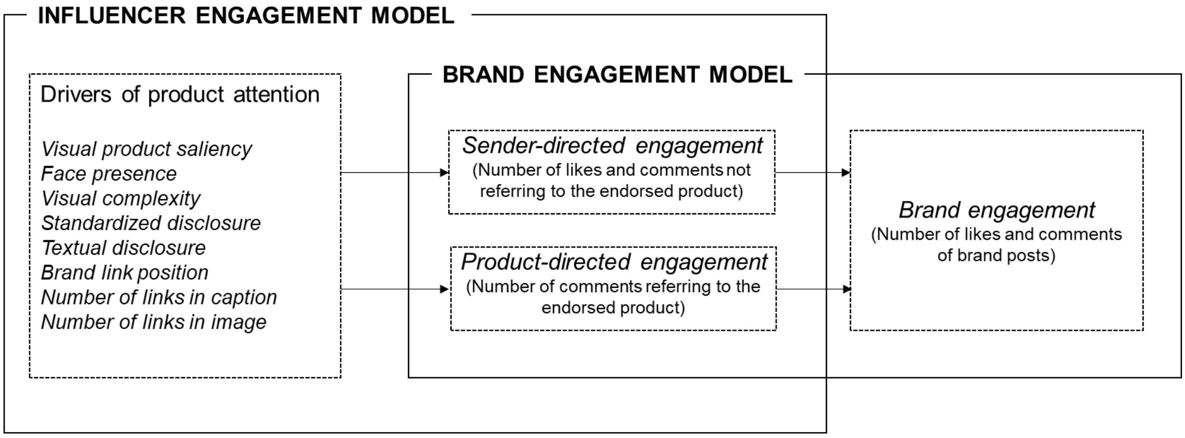

Figure 1. Conceptual framework.
Notes: Variable names are in italics.

Sample

To study the proposed relationships, we built a sample of Instagram influencer endorsement posts for two product categories, namely watches and shoes. These categories are suitable for our study given that they represent products often promoted by influencers. 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 saliency very high (i.e., an image showing only the product) or low.

Additionally, there are several brands that nearly solely sell product in one of these two categories. This 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). We collected 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. Further details on the sample collection and a statistical comparison between the two sampling methods are given in Web Appendix A. 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 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 mentioning one [1]of the selected brands, we remove 309 (5.59%) posts with a video as the visual attention of the endorsed object is not comparable to a single image. We further only considered influencers with multiple endorsement posts, which allowed us to estimate influencer fixed effects. We remove 339 (6.50%) posts from influencers with a single post.

[1] 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.

We then downloaded the images for all influencer posts linked to any of the aforementioned brands and detected all objects 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, persons, 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., 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. To make sure that all objects were found, we partitioned the original images into 299 × 299-pixel images, as this is the required size for the input matrix of the underlying InceptionV3 (Google 2020b). The Google Cloud Vision API automatically rescales input images to fit the model, but this process can lead to less accurate detection of small objects. Partitioning the images revealed 943 images with products that had not been detected in the original size. 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 of the full image). In comparison, the brand logos investigated by Hartmann et al. (2021) occupied an average of 7% of an image, which confirms that our method was able to detect small products in the images. 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.

Table 2. Sample description

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	n = 17,444

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). 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 and brand posts.

Brand Engagement Model

The aim of the brand engagement model is to present evidence on whether high post and/or product-directed engagement in the context of influencer endorsement posts actually transfers to higher brand engagement on Instagram. The brand engagement model relies on a negative binomial regression model such that:

$$\ln(E[\text{Brand\_engagement}_{ijt}]) = \alpha_0 + \alpha_1 \text{ Aggregate\_sender\_directed\_engagement}_{ijt} + \alpha_2 \text{ Aggregate\_product\_directed\_engagement}_{ijt} + \alpha_3 \text{ Control}_{ijt} \quad (1)$$

where Brand_engagement$_{ijt}$ denotes the brand engagement (i.e., the number of likes and comments) of post i by brand j in week t. Aggregate_sender_directed_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. Aggregate_product_directed_engagement$_{ijt}$ counts the aggregate number of comments referring to the endorsed product of all influencer posts endorsing brand j in week t. 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 dummies. All variables are explained in the following section.

Variables

Brand engagement

We measured brand engagement as the number of likes and comments received by a brand post. The action of liking or commenting a brand post requires the consumer to be aware of the brand and, to a certain extent, engage with its content and thus reflects two focal goals of influencer marketing (Influencer Marketing Hub 2022).

Aggregate sender- and product-directed engagement

We measured sender-directed engagement according to the number of likes and comments that do not refer to the endorsed product received by a post (Hughes, Swaminathan, and Brooks 2019). Although we cannot infer what drove each like (e.g., the sender itself, the content of the post, or the displayed product), comments could reveal the underlying motivation by explicitly referring 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") could be interpreted as engagement driven by the product itself. We consequently collected all comments and searched for words related to the product category, such as "watch" and "wristwatch" for the watch category and "shoe," "boot," or "sneaker" for the shoe product category. We translated the search words to more than 15 common languages to account for non-English comments. We manually checked 200 randomly chosen comments that included one of the search terms, and in all cases the search term referred to the product. However, we recognize that in rare cases the terms might have other meanings. We further count all comments that included the name of the endorsed brand (e.g., "I like your vans") as product-directed engagement. We measured product-directed engagement according to the number of comments explicitly referring to the product or including the brand name. While Hartmann et al. (2021) train a text classification model to classify comments into purchase intentions (yes vs. no), their approach is less suitable in our context as influencers might present more than one product that the purchase intention can refer to. Given our knowledge on the endorsed object's product category, searching for associated keywords should lead to a more accurate detection of comments related to the endorsed product. To access the content of the identified comments, we sampled 250 comments and showed them to two research assistants who were blind to the goal of the study. Their task was to evaluate 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-directed engagement is valid and does not need to be corrected for, for example, negative comments. We aggregated both forms of engagement for all endorsements post in the week t of the brand post.

Carryover effects

Brand engagement is likely not only affected from influencer sender- and product-directed engagement from the week of the brand post but potentially from all prior influencer endorsement posts, as users' decision to visit the brand page on Instagram might be made at a later stage and users who once engaged with the brand might do so again in later weeks. To account for such carryover effects, we define aggregate sender-directed engagement and aggregate product-directed engagement as stock variables such that:

$$\text{Stock}_{ijt} = \lambda \text{Stock}_{ij,t-1} + Z_{ijt}, \qquad (2)$$

where Z_{ijt} denotes either post or product-directed 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 close carryover effects for targeted advertising. Using a stock formulation also reduces a potential reverse effect from brand engagement on sender- and product-directed engagement as we assume that users do not strongly engage for 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 sender- and product-directed engagement on brand engagement requires a number of concerns to be addressed. In particular, brands might vary in their ability to generate engagement, for example as a result of previous marketing campaigns or because of differences among their followers. To account for these differences among brands, we added brand fixed effects. In addition, followers' willingness to engage with content from brands may vary over time. For example, in periods where followers have more leisure time (e.g., vacation weeks), they might be more likely to access and engage with content made available by brands. In our model, this was accounted for by using week fixed effects.

Sender- and product-directed engagement may be correlated with brand engagement shocks as brands strategically plan their social media activity including endorsement posts and owned posts. We account for several sources of endogeneity by adding a rich set of control variables that account for observable brand post characteristics as well as potential algorithmic targeting mechanisms that are controlled by the platform. Further, we control for strategic influencer selection following prior studies in influencer marketing (Hughes et al. 2019). Additionally, we use a set of instrumental variables to capture exogeneous variance in sender- and product-directed engagement of influencer posts. Control and instrumental variables are described next.

Control variables

We control for a set of potential cofounders 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) as well as complexity (Hartmann et al. 2021). To assess the visual complexity of the image, we used the method proposed by Rosenholtz, Li, and Nakano (2007), which quantifies complexity based on the whole image rather than on specific objects. Further, we control for the presence of a face (Hartmann et al. 2021). We defined face as a binary variable which is equal to 1 if there is at least one face in the image. We only counted the face if it covered at least 1% of the image. We receive the information using the Google Vision API similar to other objects detected in the image. We assume that engagement is further driven by the visual setting of the image. For example, a watch brand like Cluse might show its watch product in different settings, such as a model wearing it on the beach, in a cafe, or in the gym. Additionally, Cluse could show a person wearing the watch or just the watch laying on table (Hartmann et al. 2021). To control for these visual settings, we use the size of the objects detected by the Google Vision API and conduct a factor analysis. One factor, for example, might have high loadings for objects typically found in a Café (e.g., mug, plate, cake) and therefore control for brand engagement driven by this setting. We use the size of the objects instead of a dummy variable for each object as smaller objects might be in the background of the image and therefore not as relevant for the visual setting.

Using the text of the caption text, we control for the length of the text, the number of exclamation and question marks, as well as the number of hashtags and linked accounts. 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 B. We controlled for the number of prior posts to control for a time trend in brand engagement. We added the Google trend of the brand j in week i to control for time-varying interest in the brands offerings. We further added a dummy for each but one day of the week.

Algorithmic targeting of posts

Social media algorithms try to optimize engagement by targeting users (i.e., they show content to users that are more likely to engage; Costine 2018; Lee and Hosanagar 2018). Although Instagram shows each post to each follower, the order of posts is not chronological; rather, it is determined by the targeting algorithm. According to Instagram (Costine 2018), algorithmic targeting is based on (a) how recently the post was published, (b) past user engagement with the sender of the post, and (c) past user 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 order according to recency. To control for (b) past user engagement with the sender (e.g., the brand or the influencer), we defined a metric of abnormal prior sender-directed engagement. If prior posts received more engagement, the algorithm is likely to send the focal post to more users 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[2]. To test whether these

[2] 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.

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 users 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 C.

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 sender- and product-directed engagement as well as brand 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, Gu, and Palmatier (2022b) and Wies, Bleier, and Edeling (2022) 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 modeled 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}). 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). We further added dummies for each influencer and week to the model. The logit-model shows a significant effect of n_{kt} on s_{kt} (.880, $p < .01$). We then average the inverse Mills ratio (IMR) for all influencers endorsing brand j in week t. Details of the model are described in Web Appendix D.

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 sender- and product-directed 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 posts of the brand and the influencers. Instruments for these two variables must be relevant (i.e., strongly related to the endogenous regressors) and valid; that is, they should not directly cause changes in the dependent variable of the second stage model after all other variables are controlled for. As instrumental variables, we first used the average sender-directed engagement (i.e., average number of likes) of all posts a particular influencer k created in week t (i.e., the week of the brand post) that were not endorsing brand j. The average number of likes for these posts should be correlated with sender-directed engagement for the endorsement post since it reflects how strongly influencers have been recently in contact with their followers. Further, the average sender-directed engagement for prior posts is not likely to directly affect brand engagement as these posts are unrelated to the endorsed brand j. The prior posts could be organic posts not endorsing products (e.g., selfies of the influencer) or endorsements of other brands. In both cases, we think it is reasonable to assume that engagement with these posts should not spill over to the engagement with brand j. To control for the endogenous variance in product-directed engagement (i.e., number of comments referring to the endorsed product), we used the average number of comments of all 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 sender- and product-directed engagement) on the two instrumental variables and all other variables from the brand engagement model. Formally, we estimated a negative binomial regression model with $\ln(E[\mathrm{y}_{\mathrm{ijt}}]) = \beta_0 + \mathrm{B}_1\mathrm{X}_{\mathrm{ijt}} + \mathrm{B}_2\mathrm{U}_{\mathrm{ijt}}$, where y_{ijt} is either the aggregate influencer post or product-directed 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 stages models as regressors to control for the endogenous variance of the main variables of interest. Note that sender-directed and product-directed engagement as well as the two instruments are stock variables as described above.

Table 3. Results for first-stage models with instrumental variables

Dependent variable:	Aggregate sender-directed engagement		Aggregate product-directed 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.

After estimating the parameters, we found a significant relationship between the two instruments and aggregate sender-directed engagement as well as aggregate product-directed engagement (Table 3). In line with our expectancy, aggregate sender-directed engagement is positively affected by the number of likes of prior non-endorsement posts (1.072, $p < .01$). Further, influencers seem to generate less sender-directed engagement when their prior non-endorsement posts received more comments (-.060, $p < .01$). For aggregate product-directed engagement, the effects are the other way around. An interpretation for the negative effects is that influencers create content that is either able to generate likes or comments, but not both at the same time. For the sender-directed engagement model, including the instrumental variables increases Nagelkerke's pseudo R^2 from .633 to .983. For the product-directed 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 4. Variable correlations and descriptive statistics for brand engagement model are depicted in Web Appendix E.

Table 4. Variable descriptions for brand engagement model

Variable	Description	Mean[a]	SD[a]
Dependent variables			
Brand engagement	Number of likes and comments for each brand post	25,364	38,810
Main variables			
Aggregate sender-directed 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-directed engagement	Aggregate number of comments referring to the endorsed product/brand for posts of all influencers endorsing the brand in week of the brand post (log-transformed). Stock variable with a carryover coefficient of λ =.65.	13	31
Control functions			
$\widehat{\varphi}^{Sender}$	Pearson residual of the first-stage model for aggregate sender-directed engagement (see Table 3)	-.010	.928
$\widehat{\varphi}^{Product}$	Pearson residual of the first-stage model for aggregate product-directed engagement (see Table 3)	-.026	1.076
Algorithmic targeting			
Recency	Number of hours between post the and the next post (log)	18.234	26.547
Abnormal prior post engagement	Abnormal engagement of posts within the last three months weighted by elapsed time	-.436	3.970
Abnormal similar post engagement	Abnormal engagement of posts within the last three months weighted by Jaccard-similarity of caption text	-.029	2.113
Influencer selection			
Inverted Mills ratio	Average inverted Mills ratio from Heckman selection model for all influencers endorsing the brand in the week of the brand post	1.145	0.954
Control variables			
Colorfulness	Colorfulness of the image. Measure from Hasler (2003)	37	19

Brightness	Brightness value of the hue saturation value (HSV) color model	152	40
Visual complexity	Visual complexity of the image. Measure from Rosenholtz et al. (2007)	3.612	0.603
Face	Binary variable; = 1 if the post shows at least one face	.266	.442
Visual setting	Latent factors explaining the size of all objects detected in the image of the post	-	-
Text Length	Number of characters of the caption (log)	143	95
Number of exclamation marks	Number of "!" characters of the caption (log)	.323	.643
Number of exclamation marks	Number of "?" characters of the caption (log)	.131	.355
Number of Hashtags	Number of "#" characters of the caption (log)	2.771	4.54
Number of linked accounts	Number of "@" characters of the caption (log)	.742	.815
Text sentiment	Valence of the caption between -1 (negative) and +1 (positive) using VADER sentiment (Hutto & Gilbert 2014)	.398	.393
Coupon incentive	Binary variable; = 1if the caption contains a coupon	.006	.078
Giveaway incentive	Binary variable; = 1if the caption contains a free product giveaway	.015	.122
Number of prior posts	Number of previous posts (log).	753	571
Google trend brand	Google trend for the endorsed brand (log)	46	19
Brand dummy	Dummy variable for all but one brand	-	-
Week dummy	Dummy variable for all but one week	-	-
Weekday dummy	Dummy variable for all but one weekday	-	-

Notes: Values are calculated before log transformation.

Results

All results for brand engagement are summarized in Table 5 and discussed in the following paragraphs.

Endorsement post engagement

The results of M1 show a significant positive effect of aggregate sender-directed engagement (.014, $p < .01$) and aggregate product-directed engagement (.055, $p < .01$) on brand engagement. In terms of magnitude however, product-directed engagement shows a four times higher effect on brand engagement, indicating that influencer posts that generate high levels of product-directed engagement are better suited to drive brand engagement. As aggregate sender- and product-directed engagement are log-transformed, we can interpret the coefficients directly as quasi-elasticities to see how a 1% change affects brand engagement (Staebler & Haenlein

2021). Accordingly, a 1% change in sender-directed engagement leads to a 1.398% change in brand engagement while a 1% increase in product-directed engagement leads to a 5.717% change in brand engagement. If we estimate M1 without the residuals φ from the control function approach, both aggregate sender-directed (.017, $p < .01$) and product-directed engagement (.034, $p < .01$) have a significant positive effect on brand engagement. We now discuss our model estimates for the impact of the control variables.

Table 5. Factors that impact engagement for brand posts

Dependent variable:	M1: Brand engagement	
Constant	**7.895*****	(.144)
Endorsement post engagement		
Aggregate sender-directed engagement	**.014*****	(.003)
Aggregate product-directed engagement	**.055*****	(.007)
Control functions		
$\hat{\varphi}^{\text{Sender}}$	**-.010****	(.004)
$\hat{\varphi}^{\text{Product}}$	**-.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)
Dummy variables		
Brand	Yes	
Week	Yes	
Weekday	Yes	

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

Control variables

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

Alternate dependent variable

While brand engagement is measured as the sum of likes and comments of brand posts, one could argue that comments are even more valuable than likes as they indicate higher engagement (i.e., more effort from the user). We estimate M1 only using the comments brand posts receive and find that sender-directed engagement has no significant effect on brand engagement (.009; $p > .10$), while product-directed engagement has (.078; $p < .01$).

The results conclude that brand engagement is strongly driven by influencer posts that create high levels of product-directed engagement and less by influencer posts that create sender-directed engagement. In the next section we therefore seek to explain what drives sender- and product-directed engagement with endorsement posts.

Influencer Engagement Models

The aim of the influencer engagement models is to study the drivers of sender- and product-directed engagement. The models were based on the sample of n = 3,480 influencer posts endorsing one of the sampled watch or shoe brands. Once again, since our metrics of sender- and product-directed engagement are non-negative integers exhibiting overdispersion (Table 6), we used a negative binomial regression such that:

$$\ln(E[\text{sender\_directed\_engagement}_{ik}]) = \beta_0 + \beta_1 \text{Visual\_attention}_{ik} + \beta_2 \text{Textual\_attention}_{ik} + \beta_3 \text{Control}_{ik} \tag{3}$$

$$\ln(E[\text{product\_directed\_engagement}_{ik}]) = \gamma_0 + \gamma_1 \text{Visual\_attention}_{ik} + \gamma_2 \text{Textual\_attention}_{ik} + \gamma_3 \text{Control}_{ik} \tag{4}$$

where sender_directed_engagement$_{ik}$ denotes the sender-directed engagement (i.e., the number of likes and comments not referencing the product) of post i by influencer k. Likewise, product_directed_engagement$_{ik}$ denotes the product-directed engagement (i.e., the number of product-related comments). Visual_attention$_{ik}$ is a vector containing visual drivers of product attention, and Textual_attention$_{ik}$ contains textual drivers of product attention. Control$_{ik}$ is a vector of control variables as well as influencer, endorsed brand, week, and weekday dummies. The main variables, which are the visual and textual drivers of attention, are explained in the following section and exemplified using the post in Figure 2.

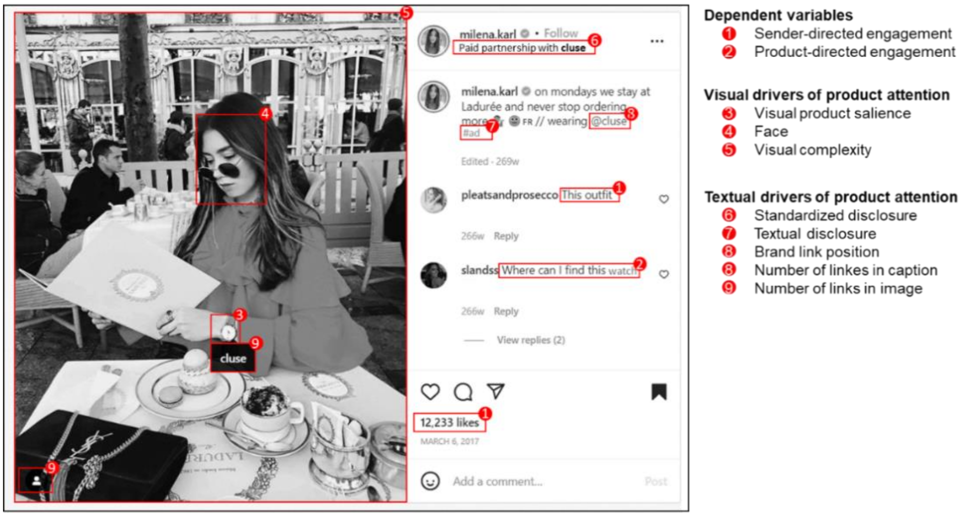

Figure 2. Dependent variables and main variables for the influencer engagement model

Variables

Sender- and product-directed engagement

As dependent variables, we used sender- and product-directed engagement defined in the same way as in the brand engagement model. On average, endorsement posts in our sample have a sender-directed engagement of 12,872 (SD = 40,953) and product-directed engagement of 4.395 (SD = 11.512). All variable correlations and descriptives are shown in Web Appendix F.

Visual drivers of product attention

We considered the following visual drivers of product attention: visual product saliency, face presence, and visual complexity. Regarding product saliency, 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 saliency map that assigns a saliency value for each pixel of the original image. We averaged the saliency 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 visual product saliency. Further, we measure the presence of a face in the same way as in the brand engagement model. 49.8% of the posts show the face of influencer. Third, we measure visual complexity the same way as in the brand engagement model. Note that the presence of a face and the visual complexity are treated as control variables in the brand engagement model as the main explanatory variable were the aggregate sender- and product-directed engagement of influencer posts.

Textual drivers of product attention

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 2, “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 2, “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 B) 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. All posts in our sample included a link to the brand (@[brand]) the influencer was endorsing. Because the brand is a cue that may drive 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 first lines. Additionally, Instagram always 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 user “expands” the text. In our sample, 51.5% of the post have a prominent brand link position. Influencers sometimes mention multiple brands and/or other user accounts in their post captions when multiple products and/or other persons are present. We therefore added the number of links in the caption as a numeric variable (2.418 on average). In addition to the caption text, influencers can link brands in the image. These brands will, however, only be shown after the users click on a black icon in the lower left part of the image (see Figure 2, "9"). We added the count of accounts linked in the image (number of links image) to the model (4.766 on average). Both, the number of brands linked in caption as well as in the image are expected to drive sender-directed engagement as both numbers indicate more persons and objects that could drive engagement. However, they might also grab attention away from the endorsed product, thus we expect them to have a negative effect on product-directed engagement.

Table 6. Main variables descriptions for influencer engagement model

Variable	Description	Mean[a]	SD[a]
Dependent variables			
Sender-directed engagement	Number of likes and comments not referring to the endorsed product	12,872	50,952
Product-directed engagement	Number of comments referring to the endorsed product/brand	4.395	11.512
Visual drivers of product attention			
Visual product saliency	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 of the image. Measure from Rosenholtz et al. (2007)	3.656	.518
Textual drivers of product attention			
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 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

Notes: Values are calculated before log transformation. Note that all control variables from the influencer engagement model that are also used in the brand engagement model are depicted in Table 4.

Identification

To identify the proposed relationship (i.e., drivers of product attention may have opposing effects on sender-directed and product-directed engagement) between the drivers of product attention and sender- and product-directed engagement, we accounted for several factors that could bias our estimates. First, we add dummies for each influencer, week, and endorsed brand to control for differences in each of our dependent variables as a function of these three dimensions. Second, we control for algorithmic targeting in the same way described above for brand posts.

Similarly, to control for the strategic selection of influencers by brands, we add the IMR to the model but instead of averaging the IMR for multiple influencer posts as in the brand engagement model we directly take the IMR that explains the selection of the respective influencer k in the week of post i. Further, we use the same control variables as in the brand engagement model such as the type of the post (giveaway and promotion), it's textual properties (e.g., sentiment, length, etc.), as well as the Google trend of the endorsed brand.

Results

All results for sender-directed engagement (M2) and product-directed engagement (M3) are summarized in Table 7 and discussed in the following paragraphs.

Drivers of product attention

Results regarding the visual appearance of the post are in line with users' attention allocation explanations. The more salient the endorsed product, the lower the sender-directed (-.022, $p < .05$) but the higher the product-directed engagement (.346, $p < .01$). Images with a face lead to higher sender-directed engagement (.121, $p < .01$) but lower product-directed engagement (-.363, $p < .01$). Lastly, visual complexity increases sender-directed engagement (.022, $p < .05$) but decreases sender-directed engagement (-.122, $p < .01$). In summary, all studied visual drivers of product attention have opposing effects on sender- and product-directed engagement.

Regarding the textual drivers of product attention, standardized disclosure has a significantly positive effect on sender- (.078, $p < .05$) and product-directed engagement (.671, $p < .01$). Textual disclosure only has a significantly positive effect on product-directed engagement (.184, $p < .01$). Taken together, sponsorship disclosure seems to increase product-directed engagement without compromising sender-directed engagement. Linking the brand directly at the beginning of the caption has a negative effect on sender-directed engagement (-.076, p < .01) but a positive effect on product-directed engagement (.265, p < .01).

Table 7. Factors that impact sender- and product directed engagement of influencer posts

Dependent variable:	M2: Sender-directed engagement		M3: Product-directed engagement	
Constant	**5.364*****	(.285)	**–2.980*****	(.989)
Visual drivers of product attention				
Visual product saliency	**–.022****	(.010)	**.346*****	(.030)
Face	**.121*****	(.020)	**–.363*****	(.060)
Visual complexity	**.022****	(.009)	**–.122*****	(.027)
Textual drivers of product attention				
Standardized disclosure	**.078****	(.031)	**.671*****	(.093)
Textual disclosure	.014	(.021)	**.184*****	(.062)
Brand link position	**–.076*****	(.019)	**.265*****	(.057)
Number of links in caption	**.135*****	(.027)	**–.283*****	(.087)
Number of links in image	.021	(.015)	**–.126*****	(.046)
Algorithmic targeting				
Recency	**.039*****	(.010)	.014	(.030)
Abnormal prior post engagement	**.075*****	(.009)	.033	(.026)
Abnormal similar post engagement	**.025*****	(.009)	–.022	(.028)
Influencer selection				
Inverse Mills ratio	**.049*****	(.018)	**–.189*****	(.050)
Control variables				
Image colorfulness	–.001	(.008)	**–.048***	(.026)
Image brightness	.002	(.009)	.010	(.026)
Caption length	**–.060*****	(.020)	–.005	(.065)
Caption exclamation marks	–.001	(.017)	–.027	(.053)
Caption question marks	.032	(.024)	**.313*****	(.069)
Caption hashtags	–.005	(.025)	–.013	(.077)
Caption sentiment	.001	(.009)	.033	(.028)
Coupon	–.019	(.025)	.051	(.078)
Giveaway	**.128****	(.052)	**.994*****	(.148)
Google trend endorsed brand	**.092***	(.050)	**.295***	(.153)
Number of prior endorsement posts	**–.073*****	(.023)	**–.174****	(.068)
Dummy variables				
Influencer	Yes		Yes	
Endorsed brand	Yes		Yes	
Week	Yes		Yes	
Weekday	Yes		Yes	

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

Linking many brands decreases product-directed engagement (-.283, $p < .01$) but increases sender-directed engagement (.135, $p < .01$). Similarly, has a negative effect on product-directed engagement (-.126, $p < .01$), while the positive effect on sender-directed engagement is not significant (.021, $p > .10$). In summary, most studied textual drivers of product attention have opposing effect on sender- and product-directed engagement. An important exception is sponsorship disclosure.

Control variables

All three variables we used to control for algorithmic targeting, recency (.039, p <. 01), abnormal prior post engagement (.075, $p < .01$), and abnormal similar post engagement (.025, $p < .01$) exert a significant effect on sender-directed engagement but no significant effect on product-directed 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 sender-directed (.049, $p < .01$) and product-directed engagement (-.189, $p < .01$), confirming the importance of controlling for it.

More colorful images receive less product-directed engagement (-.048, $p < .10$). Text length has a negative effect on sender-directed engagement (-.060, $p < .01$). In addition, the more questions are asked in the caption the more product-directed engagement is generated (.313, $p < .01$). Posts with a giveaway incentive gained more sender-directed (.128, $p < .05$) and product-directed engagement (.994, $p < .01$). 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, influencers posts gained more sender-directed (.092, $p < .10$) and product-directed (.295, $p < .10$) engagement. The number of prior product endorsement posts has a negative effect on sender-directed engagement (-.073, $p < .01$) and product-directed engagement (-.173, $p < .05$). This indicates a wear-out effect whereby multiple exposures to the same product category could reduce followers' sender-directed and product-directed engagement.

Simulation

To illustrate the magnitude of the estimated effects, we estimated the expected sender-directed and product directed engagement for five simulated influencer endorsement post that only differ regarding the drivers of product attention that are shown to have opposite effects on sender- and product directed engagement (i.e., visual product saliency, face, visual complexity, brand link position, number of links in caption, and number of links in image). We varied the values of these variables in the direction of the coefficients from the sender-direct engagement model. Post A is designed in a way that expected sender-directed engagement is very low by setting the above-mentioned variables that have a positive effect on sender-directed engagement to 10%-quantile while the variables that have a negative effect on sender-directed engagement are set to the 90%-quantile of the variable's distribution. For B ("low sender-directed engagement") we set the respective quantiles to 30% and 70%, for C ("medium sender-directed engagement") to 50% and 50%, for D ("high sender-directed engagement") to 70% and 30%, and for E ("very high sender-directed engagement") to 90% and 10%. For example, post E has a very low value of visual product saliency and the face of the influencer is visible. We then estimate the expected effect on sender-directed and product-directed engagement for a randomly chosen observations of our data. Note that this random choice only effects the absolute value of the estimates but not their relative difference. Next, we use the expected values to estimate the expected effect on brand engagement for the same week and the same brand endorsed in the post. As shown in Table 8, varying the visual and textual drivers of product attention changes the expected sender- and product-directed engagement, and in turn the expected brand engagement, strongly. In the simulated example, an endorsement post that is designed to drive sender-directed engagement (E) would lead to an estimated brand engagement decrease of -7.84% compared to the median post, while a post designed to drive product-directed engagement (A) leads to a brand engagement increase of 3.60% compared to the median post and an increase of 11.4% in comparison to (E). We further provide an example post from our sample for each post A to E based on the post with the most similar visual properties (i.e., minimum Euclidean distance for the visual product saliency, face, and visual complexity variables).

Table 8. Predicted brand engagement for endorsement posts with high sender- vs. product-directed design

Endorsement post	A	B	C	D	E
Expected sender-directed engagement	Very low	Low	Medium	High	Very high
Expected product-directed engagement	Very high	High	Medium	Low	Very low
Predicted sender-directed engagement compared to C	−6.29%	−2.89%	0.00%	33.01%	54.10%
Predicted product-directed engagement compared to C	86.78%	29.47%	0.00%	−64.31%	−81.15%
Predicted brand engagement compared to C	3.60%	1.46%	0.00%	−3.46%	−7.84%
Example endorsement post[a] – watch					
Example endorsement post[a] – shoe					

Notes: a) Examples images are chosen based on the lowest Euclidean distance between the visual drivers of product attention of the simulated post and the observations in our sample. Note that the simulated posts also vary regarding the textual drivers of product attention.

General Discussion

As recently noted by Leung et al. (2022b, p.38), "not every form of engagement is created equal." Based on this insight, we asked a fundamentally relevant question for brands that use influencer marketing: When do influencer endorsements drive brand engagement? To study these questions, we investigated the extent to which engagement with brand posts on Instagram can be explained by engagement with influencer posts that endorse the respective brand. We find that influencer posts with higher sender-directed engagement lead to higher levels of brand engagement. However, influencer posts with high product-directed engagement exert a four times stronger effect on subsequent brand engagement. We also investigated how the textual and visual design of an endorsement post explains sender- and product directed engagement. We find that features that direct attention towards the endorsed product often have opposing effect on sender- and product-directed engagement. For example, the saliency of the endorsed product leads to higher levels of product-directed but lower levels of sender-directed engagement. As a consequence, influencer endorsements maximizing sender-directed engagement will generate lower levels of product-directed engagement and thus also lower levels of brand engagement. The results cast doubt on whether practitioners' and academic researchers' current focus on sender-directed engagement in the domain of influencer marketing is sufficient.

Theoretical Contributions

The present research contributes significantly to the literature on influencer marketing by examining the downstream consequences of consumer engagement with influencer endorsement posts. Our study reveals that both sender-directed and product-directed engagement positively influence brand engagement, but the effect of product-directed engagement is much stronger than that of sender-directed engagement. We also identify several opposing effects of the endorsement post design on sender- and product-directed engagement, emphasizing that creating sender-directed engagement may not always align with the objective of building brand engagement.

Furthermore, our research introduces a straightforward measure of product-directed engagement that can be used to evaluate the effectiveness of influencer marketing. This measure, which counts the number of comments referencing the endorsed product or brand, can potentially provide managers with a valuable tool for tracking the downstream consequences of endorsement posts sponsored by other brands, and for evaluating and selecting new influencers. For researchers, this measure offers an alternative outcome variable that is more strongly linked to brand engagement than sender-directed metrics and that can be used to evaluate the effectiveness of different design and influencer choices.

Our study contributes to the literature on visual social media communication by investigating how the visual and textual design of an endorsement post drives sender-directed and product-directed engagement. As Hughes, Swaminathan, and Brooks (2019) emphasized, followers are expected to interpret an endorsed post differently depending on how the information is presented. We investigated three visual drivers of product attention that substantially influence product-directed engagement created through posted images. Product saliency (product size, brightness, and centrality) draws attention towards products and is shown to enhance product-directed engagement but reduce sender-directed engagement. Likewise, visual complexity has no effect on sender-directed engagement but significantly reduces product-directed engagement as images are less product-focused. Images showing faces have positive effects on post liking but substantially reduce the number of product-directed comments. We also investigated several textual drivers of product attention that direct attention towards endorsing brands. In line with predictions from vision research, prominent positions of brand mentions enhance product-directed engagement but show a significantly negative effect on sender-directed engagement. Likewise, links to other content in the caption text or the image decrease product-directed engagement as they draw attention away from the endorsed product.

Consequently, our analysis of textual and visual drivers of product attention points to a basic conflict between influencers and brands. Many of the factors that influencers can use to enhance sender-directed engagement (such as creating an image that shows the influencer) draw attention away from the endorsed product. Thus, creating sender-directed engagement often comes at the expense of creating less product-directed engagement. However, as our empirical results show, brands are advised to care more about product than sender-directed engagement.

Finally, there has been an ethical debate stressing that some influencers fail to reveal brand sponsorship, thus creating the impression that the created posts are organic. Our empirical results suggest that this influencer tactic does not pay off, as we found a positive effect of sponsorship cues on both sender- and product-directed engagement. While the investigated disclosure cues (standardized disclosure and textual disclosure) are partially specific to Instagram, our findings suggest that the higher the visibility of these cues, the more engagement with the post and the product can be expected. An explanation for the former might be that followers evaluate a persuasion attempt as fairer and less manipulative if the post includes a disclosure (in line with Karagür et al.'s (2022) finding that followers appreciate advertising transparency; see study 3).

Managerial Implications

Our research has strong implications for how marketers select influencers as well as how they design the incentive structure based on which influencers are paid. First, our results suggest that measuring the performance of endorsement posts, selecting influencers, and compensating influencers *solely* based on how much sender-directed engagement they create might lead to inefficient decisions. Instead, product-directed comments can be used to additionally measure engagement related to the endorsed product. As such comments are a stronger predictor of brand engagement and are thus assumed to capture an important facet of the effectiveness of influencer endorsement posts. Managerial decisions could profit from extending the focus from sender-directed to product-directed engagement. If conversion rates cannot be reliably tracked back to the specific endorsement post or conversion is not a key outcome measure (for example, if the goal is to increase brand awareness), we suggest that managers use product-directed engagement as an additional metric to access the effectiveness of an influencer post. Further, while firms can easily observe product-directed engagement for influencers they are not cooperating with, information about these influencers' conversion rates might be unavailable. Therefore, product-directed engagement might be a suitable metric to select new influencers. The proposed metric of product-directed engagement is also valuable for researchers as it is publicly available. Additionally, most social media and blogging platforms have a comment function which allows the proposed method to be used on data from platforms other than Instagram. When respective brand engagement data is available, we suggest researchers to additionally investigate the effect of aggregate influencer activity on brand engagement.

Second, our empirical results provide evidence that the goals of marketers and influencers might be conflicting, assuming that influencers' primary interest is to increase sender-directed engagement whereas brands aim to enhance brand engagement. Leung et al. (2022b), for example, suggest that marketers "should encourage influencers to make the sponsor brand more salient in the posts, by incorporating clickable brand mentions and URL links" (p. 35). Our results are fully in line with this suggestion and are based on the valuable empirical insight that textual cues that increase attention to the endorsed brand and product are drivers of product-directed engagement. While most drivers of product attention we studied had opposing effects on sender-directed and product-directed engagement, sponsorship disclosure seems to enhance both. In our data, only 10.8% of the posts have a standardized disclosure badge and 36.35% of the posts have a textual disclosure (e.g., #ad). Our results show that hiding disclosure information decreases sender- and product-directed engagement and is thus neither advisable from an influencer's nor a firm's point of view.

Third, our empirical findings guide managers in designing endorsement posts that are suited to drive brand engagement. Table 8 illustrates how the choice of the visual and textual post design affects sender- and product-directed engagement with influencer posts and how these endorsement posts, in turn, drive engagement for the endorsed brand. Our simulation shows that an endorsement post design that focuses on increasing product-directed engagement could have a 11.9% uplift in brand engagement compared to an endorsement post focusing on increasing sender-directed engagement.

Further Research and Limitations

Our study is subject to several limitations that pave the way for future research. First, it focuses on better understanding how brand engagement is created in the context of influencer marketing. While practitioners do indeed emphasize this goal, a more comprehensive analysis of how influencer endorsement posts affect different stages of the marketing funnel would help mold a more holistic assessment of the effectiveness of influencer marketing. Future researchers might thus investigate the effects of influencer endorsements on brand awareness, brand engagement, and actual sales and how these outcomes affect each other. For example, while we found that sender-directed engagement is less strongly related to brand engagement, it might still be a driver of brand awareness as more likes lead to higher reach of the post through algorithmic targeting. Other forms of sender-directed engagement, such as the number of shares (which is not publicly available on Instagram), might even be a more effective driver of brand awareness as they capture virality (Akpinar and Berger 2017).

Second, 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 sender-directed engagement seems to be particularly important when starting a new social media channel, as studies show that creating sender-directed engagement is an essential mechanism that helps influencers to build their follower base (Driessens 2013). Moreover, followers may respond differently to influencers creating product-directed engagement as followers' expectations of how much commercial content an influencer shares might depend on popularity. We suggest that future research should investigate to what extent the influence of sender- and product-directed engagement on brand engagement might change and evolve as a function of the popularity of an influencer.

Third, several factors shown in the literature to drive sender-directed engagement (see Table 1) might have weaker or even opposing effects on product-directed and brand engagement. For example, while Wiess et al. (2022) show that medium sized influencers are most effective in driving sender-directed engagement, might micro influencers <u>be</u> even more effective in driving brand engagement? We thus encourage future research to investigate which characteristics of the influencer and their endorsement posts drive brand engagement effectively. We hope our work stimulates further research on the relationship between influencer endorsements and brand engagement.

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