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The effects of visual congruence on increasing consumers' brand engagement: An empirical investigation of influencer marketing on instagram using deep-learning algorithms for automatic image classification

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A R T I C L E I N F O

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A B S T R A C T

Influencers are non-celebrity individuals who gain popularity on social media by posting visually attractive content (e.g., photos and videos) and by interacting with other users (i.e., Followers) to create a sense of authenticity and friendship. Brands partner with Influencers to garner engagement from their target consumers in a new marketing strategy known as "Influencer marketing." Nonetheless, the theoretical underpinnings of such remains unknown. We suggest a new conceptual framework of "Visual-Congruence-induced Social Influence (VCSI)," which contextualizes the Similarity-Attraction Model in the Social Influence literature. Using VCSI, we delineate how Influencers use visual congruence as representations of shared interests in a specific area to build strong bonds with Followers. This intimate affiliation catalyzes (i.e., mediates) the positive effects of visual congruence on Followers' brand engagement. To test these hypotheses, we conducted in vivo observations of Influencer marketing on Instagram. We collected >45,000 images and social media usage behaviors over 26 months. We then applied deep-learning algorithms to automatically classify each image and used social media analytics to disclose hidden associations between visual elements and brand engagement. Our hypothesis testing results provide empirical support for VCSI, advancing theories into the rapidly growing fields of multimodal content and Influencer marketing.

1. Introduction[1]

"Influencers" are ordinary individuals, not celebrities, who have amassed large numbers of Followers on social media sites by posting visually attractive content that showcases their lifestyle and merchandise preferences (Cotter, 2019). "Followers" are those individuals who subscribe to Influencers' content, and some Influencers boast tens of thousands of Followers, creating "fandom" (Abidin, 2018). Unlike celebrities, Influencers cultivate a sense of intimacy among their Followers through sharing authentic and lived experiences in the areas in which they claim expertise (Cotter, 2019). The growth of mobile applications for image-sharing, such as Instagram, has fueled the rise of Influencers (Marwick, 2013). These Influencers have surpassed celebrities as the favorite social media personalities among millennials, who have become the largest purchasing age group in the U.S. since 2019 (Fry, 2018). Recognizing millennials' purchasing power, brand managers collaborate with Influencers who have built fame in brand-pertinent areas, hoping to connect with large crowds of consumers in their niches (Abidin, 2018). An example is the beauty brand, Glossier, which enlists make-up experts to showcase Glossier products in the brand's social media posts (Ravi, 2018). Glossier is valued at 1.2 billion USD as of November 2019 (Roof & Chernova, 2019).

Nonetheless, academic research on Influencers is lagging in three intertwined aspects. First, most prior studies have focused on textual

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[1] The followings are the abbreviations used in this paper:Similarity-Attraction Model: SAMSocial Influence: SIVisual Congruence-Induced Social Influence: VCSIFollowers' engagement with their Influencers' posts: F–I engagementFollowers' engagement with posts of the Brand endorsed by their Influencers: F–B engagement

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comments, omitting visual elements in posts due to the challenges in analyzing a large number of images posted daily. Second, this omission of visual elements in the research literature hinders systematic, in vivo observations involving the effectiveness of Influencers because Influencers employ images and photos as their primary means of gaining visibility among their Followers (Cotter, 2019). The lack of in vivo observations in turn limits the supply and availability of empirical support to facilitate theory advancement. As a result, a theoretical framework to explain Influencers' roles in increasing consumer brand engagement has yet to be fully explicated. Closing the gaps in these three areas is therefore pivotal in expanding our understanding of the rapidly growing Influencer marketing. This growing field of research requires rigorous testing and firm grounding in its theoretical foundations.

To close the first and second gaps ([i] the absence of image analysis and [ii] the in vivo observations of Influencers), we employed both deep-learning algorithms and social media analytics. Deep-learning algorithms, the best-known example being Convolutional Neural Networks (CNN), have recently emerged as a robust method for classifying large numbers of images (LeCun, Bengio, & Hinton, 2015). We collected visual elements in Influencers' and their Followers' posts (>45,000 images). We then classified the themes of each collected image by fine-tuning three pre-trained CNN models. Simultaneously, we collected Influencers, their Followers, and the endorsed brand's social media data from Instagram over a data collection period of 26 months. Next, we identified associations underlying how Influencers affect their Followers' brand engagement via visually attractive content, employing social media analytics. These social media analytics allow us to identify hidden patterns in the "Big Data" collected from real-world observations (Aral & Walker, 2014).

The use of this expansive methodology renders empirical support that warrants adequate grounding in proposing a theoretical framework for Influencers' effectiveness. In particular, we contextualize the Similarity Attraction Model (SAM) in the Social Influence (SI) literature. SAM suggests that shared attitudes, interests, and opinions are predictive of frequent interactions and affiliations between two parties in a dyadic relationship (Byrne, Griffitt, & Stefaniak, 1967). Similarity in SAM has traditionally been operationalized from textual comments, which impedes SAM from being applied to multimodal elements that are increasingly prevalent in social media posts (Highfield & Leaver, 2016). Empowered by the deep-learning algorithms and social media analytics mentioned above, we propose a new concept, *visual congruence*, which denotes the extent to which the themes of images posted by two parties overlap. We then argue that Influencers carefully curate visual congruence in their posts in order to accentuate shared interests with their Followers in their attempts to attract these Followers to their content, based on SAM.

Next, we posit that these increased affiliations between Influencers and Followers induce Followers to engage with the brand's posts that Influencers endorse, based on the SI literature. SI refers to the influences that individuals exert on the ways in which others expect a product's utilities (Godes et al., 2005). SI augments the propagation of ideas and economic behaviors throughout social networks (Aral & Walker, 2014). One's SI on the other party in a dyadic relationship increases when the two parties are engaged in frequent and intimate interactions (Aral & Walker, 2014). Thus, we argue that frequent interactions, which Influencers garner from their Followers through creating visual congruence, facilitate Followers' brand engagement. Accordingly, this framework suggests the mediating role of strong affiliations between Influencers and their Followers in catalyzing the positive impact of visual congruence on Followers' brand engagement. To denote the new mechanisms of conducting influence through visual elements, mediated by increased interactions, we suggest "*Visual Congruence-induced Social Influence*."

In conclusion, we extend the application of SAM from textual to visual realms and contextualize SAM into SI to delineate the process by which visual congruence increases Followers' engagement with the brand. In so doing, we contribute to knowledge advancement in not only the Influencer marketing field but also SAM and SI. We also propose an expansive methodology that will aid in future researchers who are challenged in their pursuit of this rapidly growing, yet understudied area due to technical difficulties.

2. Background

2.1. Growth of influencers

In order to amass and maintain a large number of Followers, Influencers create *visually attractive content in a niche area in which they claim expertise* (Lueck, 2015). Well-known examples of these niches include health (specialty foods and cooking), beauty (fashion and makeup), fitness (workout and body images), and video games (Abidin, 2016; Park, Ciampaglia, & Ferrara, 2016). There is a growing need among social media users to learn from other ordinary people's authentic experiences in these areas of interest, rather than from celebrities' artificial illustrations (Cotter, 2019). By demonstrating the "realness" in these areas, Influencers cultivate a sense of intimacy and relatability, which garners *Followers' engagement with their content* (Cotter, 2019).

These strong bonds that Influencers have built with their Followers (equivalent to "fandom") have caught the attention of brand managers who are looking for effective, yet cost-efficient ways of promoting their brands (Park et al., 2016). Brand managers approach Influencers who are famous in the areas pertinent to their brands. Moreover, these brand managers give Influencers complimentary products and invite them to exclusive events (Agrawal, 2016; Contestabile, 2018; De Veirman, Cauberghe, & Hudders, 2017).

Through these opportunities, brand managers strive to foster Influencers' brand loyalty, thereby enticing them to showcase the branded products in their social media posts. This frequent brand placement is anticipated to garner favorable brand attitudes among Influencers' Followers (De Veirman et al., 2017; Yu, Jiang, & Ko, 2017). One example of a brand that has utilized Influencers to its advantage is the beauty brand, Glossier. As a part of its branding, Glossier enlists the help of "brand ambassadors," or specifically chosen Influencers to post images of themselves using Glossier products on their own pages (Ravi, 2018). Through the Influencers' impact on their own loyal Followers, Glossier is now valued at over 1.2 billion USD (Roof & Chernova, 2019).

Recall, however, that being viewed as "real," and not just as a paid advertiser, is critical to an Influencer's success in obtaining and maintaining prominent Influencer status (Abidin, 2018). Oftentimes successful Influencers pick and choose the brands they partner with, according to their own personal images in order to maintain their sense of authenticity and credibility for their Followers (Abidin, 2018). As such, <u>brand endorsements on Influencers' pages are indirect, integrated into their lifestyle choices, and are made in passing</u>.

One of the most popular sites for Influencers is Instagram. On Instagram, Influencers post photographs of themselves using a product and describing their experience. According to a Pew study, 37% of all adults and 67% of individuals aged 18–29 years old in the U.S. use Instagram, and its user base continues to grow (Perrin & Anderson, 2019). Millennials—those born between 1981 and 1996—are especially drawn to Influencers. For example, in a Nielsen study of celebrity marketability, the beauty Influencer Michelle Phan was more likely to be a male survey respondent's favorite personality over actresses or sports stars (Nielsen Research, 2017).

Millennials are spending more time on Instagram via their phones and are more likely to make purchases directly from their phones (Nielsen Research, 2019). Millennials are projected to be the largest generational cohort from 2019 and going forward, surpassing baby boomers as the most substantial purchasing age group (Fry, 2018). Recognizing the importance of millennials, in 2019, Instagram partnered with selected brands and Influencers to allow users to shop for items directly from an Influencer's post. This reliance on Influencers to bring in shoppers is expected to contribute 10 billion USD in revenue for

Instagram in 2021 (Lorenz, 2019).

2.2. Review of the literature

Despite the rapid expansion of Influencer marketing, there is a paucity of quantitative, in vivo examinations of its effects on Followers' brand engagement. Granted, several studies have examined Influencers, but most of them are ethnographic and qualitative studies defining Influencers (Marwick, 2015a; 2015b) and resultant social trends and concerns (Abidin, 2016). Studies in the recently emerging area known as "Critical Algorithmic Studies" have paid attention to the types of algorithmic skills that Influencers need in order to gain visibility in fierce competition with others (Bishop, 2019; Cotter, 2019; Klawitter & Hargittai, 2018). Also, research in Advertising has investigated how brands improve images and connect with consumers by leveraging Influencers' fandom (De Veirman et al., 2017; Jin & Muqaddam, 2018; Uzunoğlu & Kip, 2014).

Yet three issues remain unresolved. First, most prior studies have paid attention to textual narratives while omitting *visual content that Influencers use to garner their Followers' engagement*. Despite the rapid growth of image-sharing applications, academic investigation into visual content is lagging due to the technical challenges involved in analyzing thousands of images posted daily (Song, Han, Lee, & Kim, 2018). Deep-learning algorithms have recently been proposed as a viable option that lowers the costs and time necessary to undertake this challenge (He, Zhang, Ren, & Sun, 2016; LeCun et al., 2015). Second, the current literature lacks *a systematic, quantitative, and* in vivo *analysis regarding the effectiveness of Influencer marketing.* Third, *no clear theoretical framework has been suggested* to explain how Influencers can affect their Followers' long-term brand engagement.

This study aims to fill the above mentioned three gaps in the literature ([i] the omission of visual elements in the analysis, [ii] the lack of a quantitative, in vivo analysis regarding the effectiveness of Influencer marketing, and [iii] the lack of a theoretical framework). *First*, to analyze the themes of the posts' visual elements collected in the real world, we employ three open-source deep-learning algorithms based on Convolutional Neural Networks (CNN) (LeCun & Bengio, 1995). *Second*, we use social media analytics to quantitatively test these hypotheses from over two years of in vivo observations involving Influencers, their Followers, and the brand. *Third*, for the theoretical underpinnings, we contextualize the *Similarity-Attraction Model* (Byrne et al., 1967; Montoya & Horton, 2013; Youyou, Stillwell, Schwartz, & Kosinski, 2017) in the *Social Influence* literature (Aral & Walker, 2014; Godes et al., 2005). This contextualization allows us to explain how attitudinal similarity manifested in images enables Influencers to gain Followers' engagement in their content, and how they subsequently induce their Followers to engage in a specific brand. By successfully filling these gaps, this study provides one of the earliest quantitative attempts to provide *in vivo* empirical support for Influencers' positive roles in increasing brand engagement within a firmly grounded theorical framework.

3. Theoretical foundation

3.1. Contextualization of the Similarity-Attraction Model in the social influence literature

As the overarching theory of our investigation, we chose SAM, which goes back to Newcomb in his 1956 work on the prediction of interpersonal attraction. In that work, Newcomb claimed that attitudinal similarity is the strongest predictor of interpersonal relationships. Inspired by Newcomb's work, Byrne and his associates have conducted extensive studies over three decades and have confirmed the importance of similarity in attraction: "the expression of similar attitudes by a stranger serves as a positive reinforcement because consensual validation for an individual's attitudes, opinions and beliefs is a major source of reward …" (Byrne, Nelson, & Reeves, 1966, pp. 98–99).

The application of SAM has been expanded to online and digital interactions between individuals and between individuals and technical artifacts (Al-Natour, Benbasat, & Cenfetelli, 2011). Jensen, Davis, and Farnham (2002) found that people value similarity information most when selecting whom to interact with in online environments. Individuals value "fit" with themselves. Similarity is a strong predictor of building connections online (Jensen et al., 2002). Al-Natour et al. (2011) conducted an online experiment and found that perceived personality similarity between the recommender system and its users, with respect to dominance and submissiveness, increases users' perceived enjoyment, social presence, and trust toward the virtual recommendation agents.

We posit that SAM serves as an adequate theoretical support for our study, given that Influencers earn their Followers' engagement based on their common interests in niche areas, as explained in Section 2.1. Particularly in social media, people follow others who are similar to them in terms of interests and preferences (Aiello et al., 2012). This "birds of a feather flock together" tendency (McPherson et al., 2001) becomes more prevalent in social media, given the vast array of options that a social media user has from which to choose. Audiences simply turn away from voices that do not resonate with their own (Teng, Khong, Goh, & Chong, 2014). Posting messages about issues in which Followers are not interested lowers their engagement with such messages (Malhotra, A., Malhotra, C., & See, 2013).

Thus, we apply the main tenant of SAM to Influencer marketing. However, SAM does NOT fully explicate the phenomena under our investigation in two aspects: whether (i) similarity can be perceived based on images only, *sans* narratives, and whether (ii) similarity can influence Followers' engagement with the brand. Thus far, similarity in SAM has been established on the basis of narratives and conversations (Byrne, 1997). For instance, people often find personality similarities with others after engaging in conversations (Byrne et al., 1967). However, Instagram and other image-sharing applications require no textual input from a post. Thus, a user often posts an image without any text or hashtag (Song et al., 2018). To encompass these growing posting behaviors, we propose a concept of visual congruence defined herein as a match between the themes of the visual elements in Influencers' and their Followers' posts. According to this definition, if two parties in a dyadic relationship frequently post images whose themes are highly related, relevant, and similar to those of each other's, we say that visual congruence exists between the two parties' posts. This visual congruence suggests *a high likelihood that the two parties have similar attitudinal values, interests, and beliefs, given that people post images that are relevant to their interests* (Song et al., 2018). As a result, the two parties will become attracted to each other. In Influencer marketing, where an Influencer has high in-degree centrality, Followers will be more attracted to the Influencer. We investigate whether this visual congruence would induce Followers' engagement, thereby expanding SAM from the textual to the visual realms.

Second, we expand SAM by identifying *the processes by which visual congruence increases Followers' engagement with the brand.* SAM provides a theoretical grounding for Followers' attraction to Influencers' posts but does not explain whether or not this attraction will *affect* their behaviors toward the brand, which is one degree of separation from the Influencers. According to the definition of Influencers (summarized in Section 2.1), the authenticity and "realness" of Influencers keep Followers *engaged* in the Influencers' posts, and *this continued engagement subsequently induces brand engagement among Followers*. The second half of this relationship is above and beyond the boundary conditions of SAM.

Thus, we suggest the concept of *Social Influence* (Aral & Walker, 2014; Godes et al., 2005). SI is recognized as a key factor in propagating ideas and economic behaviors in digital networks (Aral & Walker, 2014). SI is defined as "an action or actions that is taken by an individual not actively engaged in selling the product or service and that impacts others' expected utility for that product or service" (Godes et al., 2005, pp. 416–417). This definition fits well with the definition and roles of

Influencers in our study because we anticipate Influencers to affect their Followers' brand engagement without being actively engaged in selling the brand. Another definition of SI by Aral (2011, p. 217) is the following: "how the behaviors of one's peers change the likelihood that (or extent to which) one engages in a behavior." Aral's definition again fits well with the purpose of this study: product showcasing in Influencers' posts changes the extent to which their Followers engage with the brand's posts. Thus, we selected SI to explain how Followers' engagement in Influencers' posts is translated into increased brand engagement. In conclusion, we suggest an expanded conceptual framework, "Visual-Congruence-induced Social Influence (VCSI)," to delineate how visual congruence as representations of shared interests enables Influencers to induce their Followers' brand engagement by fostering their affiliations with their Followers. To the best of our knowledge, no prior study has identified this behavioral mechanism underlying the effectiveness of Influencer marketing for brand engagement.

3.2. Methodological expansions and contributions

In order to examine VCSI, we used social media analytics, accompanied by deep-learning algorithms. We provide detailed descriptions of our methodology in Section 5, but in this section, we explain how our chosen methodology allows for theory advancement in VCSI.

Social media analytics expand our understanding of human behavior, for both marketers and social scientists (Aral & Walker, 2014). These analytics allow us to find hidden patterns in "Big Data" in unprecedented sizes, scales, and modalities for our observations (Mayer--Schonberger & Cukier, 2013). By identifying associations in the behavioral mechanisms underlying the outcomes of Influencer marketing, we can develop more contextualized and effective branding strategies.

Given the rapid growth of image-exchange among millennials, effective social media analytics increasingly require the consideration of multiple content modalities. In response, we suggest deep-learning algorithms, such as CNN, that have emerged as a dominant approach in the computer vision field (LeCun & Bengio, 1995; LeCun et al., 2015). The advantages of CNN entail its ability to automatically detect visual features *without* human supervision and its robust performance, surpassing hand-crafted feature description algorithms (e.g., scale-invariant feature transformation) (Lowe, 2004). There are several open-source CNN models that were initially pretrained with an ImageNet dataset as a benchmark, and were fine-tuned for various datasets outside the ImageNet dataset (He et al., 2016; Simonyan & Zisserman, 2014; Szegedy, Vanhoucke, Ioffe, Shlens, & Wojna, 2016). These models provide robust and cost-efficient means for investigation into visual content in various forms, areas, and topics.

In addition, the combined use of social media analytics with deep-learning algorithms has other advantages in developing VCSI. It allows us to overcome the limitations of relying on self-reporting methods. Many Followers may not recognize or admit the exact reasons for their affiliations with Influencers or increased brand engagement. For instance, they may not know that they are attracted to their Influencers' posts because of visual congruence that the Influencers carefully crafted. Thus, the use of social media analytics, accompanied by deep-learning algorithms, allows us to identify hidden behavioral patterns and associations with unobstructed observations that are necessary for developing VCSI (Shin et al., 2016; Weiss, Khoshgoftaar, & Wang, 2016).

4. Hypothesis development

Fig. 1 delineates our research model. We argue that visual congruence, manifested in Influencers' posts with their Followers in the areas that are pertinent to the brand, will increase Followers' engagement with the Influencers' posts (H1), and in turn with the brand's posts (H2).[2] In addition, we maintain that the positive influence of visual congruence on Followers' brand engagement will be fully mediated by their engagement with Influencers (H3). That is, visual congruence will have positive effects on brand engagement only when Followers are engaged with their Influencers' content. We provide detailed grounds for these assertions in subsequent sections (Sections 4.1 and 4.2). For the sake of precise descriptions, we use abbreviations, such as F–I engagement and F–B engagement, to denote Followers' engagement with Influencers' posts and Followers' engagement with the brand's posts, respectively.

4.1. Impact of visual congruence on followers' engagement

We maintain that visual congruence will increase F–I engagement, based on SAM. Similarity is known to be the strongest predictor of interpersonal relationship formation (Byrne et al., 1967). In online social networks, people seek interactions with others who not only share similar socioeconomic status, but also similar values, attitudes, beliefs, and aspirations (Gu, Konana, Raghunathan, & Chen, 2014). As such, Followers will tend to be drawn to the posts of Influencers with similar interests.

In particular, congruent opinions between the message source and recipients are strong attractors, given that congruence in opinions implies that they have similar attitudinal values and perspectives (Shore, Baek, & Dellarocas, 2018). *Instagram users express their opinions and interests in the images they post* (Song et al., 2018). Song et al. (2018) have shown that teenage users post more human-related images (e.g., faces), while older users post more nature-related images (e.g., scenery). Moreover, they found that analyzing images alone predicts users' characteristics more accurately than narratives, and an analysis of both images and text combined did not outperform the image-only analysis (Song et al., 2018). As such, we posit that the visual congruence between Influencers and their Followers will indicate a high likelihood that Influencers have interests and opinions similar to those of Followers in selected fields.

Williams, Petrosky, Hernandez, and Page (2011) have empirically shown that an image can represent consumers' interests, and that congruence (in terms of the visual themes) can induce consumers to purchase products. Specifically, consumers interested in a popular application would purchase a copycat application when presented with an image similar to the application (Williams, Petrosky, Hernandez, & Page, 2011). Thus, although Williams et al. (2011) have *not* shown the impact of visual elements on Followers' engagement, their study provides general empirical support for the positive effects that similarity in posted visual elements has on consumer behaviors.

Based on SAM and Williams et al. (2011)'s empirical findings, we argue that when an Influencer's content overlaps with Followers' interests, Followers will be more likely engaged with the Influencer's content than when the content does not overlap:

Hypothesis 1. Higher visual congruence is positively associated with Followers' engagement in Influencers' posts.

Next, we posit that an increase in F–I engagement will lead to an increase in F–B engagement. Recall that Influencers feature brands in their posts in a way that is subtle and indirect (Section 2.1). As Followers are more

[2] In this study, "engagement" refers to one dimension—i.e., the behavioral engagement—of consumer brand engagement (CBE) concept that consists of cognitive, emotional, and behavioral dimensions (Brodie et al., 2011). Our study employed a data-driven approach; thus, we focused only the behavioral dimension of engagement observable in social media data.

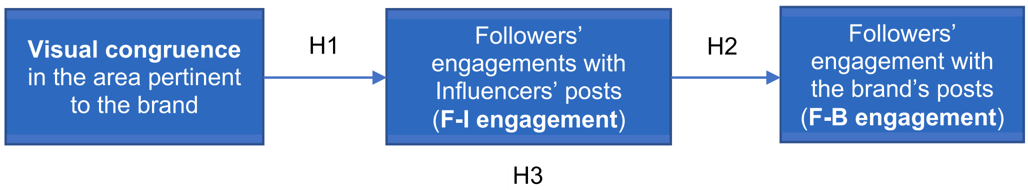

Fig. 1. Research Model. Our research model contains three hypotheses, one of which posits the mediating role of F–I engagement between visual congruence and F–B engagement.

engaged in their Influencers' content that features the brand, Followers' perceived familiarity with the brand will increase, even though an explicit brand endorsement is absent. The effectiveness of seemingly unintentional product placement (aiming to increase consumers' exposure to the product) is widely known in advertising (Williams, Petrosky, Hernandez, & Page Jr., 2011). Familiar objects are accepted with ease and with less resistance from recipients, thus bypassing the rigorous verification often required when accepting an unfamiliar object (Ecker, Lewandowsky, Oberauer, & Chee, 2010; Evans & Stanovich, 2013; Pennycook & Rand, 2018). In addition, since the audience members have developed positive attitudes toward the Influencer's content, they anticipate similarly likeable content from the brand (Jin & Phua, 2014). Accordingly, Followers are more likely to adopt Influencers' prosocial behaviors toward the featured brand (Jin & Phua, 2014). We argue that prosocial behaviors toward the brand will be manifested in the forms of engaging with the brand's posts in case of Influencer marketing.

The credibility of a message source is known to be a predictor of message acceptance in advertising (Bhatt, Jayswal, & Patel, 2013; Lee, Lee, & Hansen, 2016; Tormala & Petty, 2004). As such, many advertisers have employed celebrities who are considered to be credible in spreading their brand messages. Since Influencers have obtained micro-celebrity status on Instagram and have earned their Followers' engagement, we can expect that they have also earned credibility from their Followers, which will cultivate positive brand attitudes among the Followers. Jin and Muqaddam (2019) have shown that Influencers who feature a brand increase customers' perceived credibility, likeability, and attractiveness of the brand. Jin and Muqaddam (2019) employed an online experiment where subjects were presented with, among others, (i) Instagram images featuring Influencers and the brand, and (ii) Instagram images featuring the brand only. The results have shown that brand credibility, attractiveness, and likeability were higher when the images contained both the Influencer and the brand than the product only (Jin & Muqaddam, 2019).

Based on the positive impact involving (i) the familiarity of stimuli on message acceptance and (ii) the credibility of Influencers on their Followers' brand attitudes, we argue that Followers' engagement with Influencers will garner their engagement with the brand's posts. Therefore, we hypothesize the following:

Hypothesis 2. Followers' engagement with Influencers' posts will increase Followers' engagement with the brand's posts endorsed by the Influencers.

4.2. Mediating role of followers' engagement with influencers between visual congruence and brand engagement

So far, we have hypothesized that visual congruence will be associated with an increase in F–I engagement, which in turn will increase F–B engagement. In this section, *we posit the mediating role of F–I engagement in the relationship between visual congruence and F–B engagement*. SAM does not sufficiently explain or predict that Influencers can positively affect their Followers' decisions or behaviors to engage with the brand's posts because two parties in a dyadic relationship can be simultaneously attracted to a brand due to their common interests (Aral & Walker, 2014). Thus, visual congruence alone is limited to solely rendering F–B engagement. Instead, we argue that visual congruence must be accompanied by F–I engagement to have a positive impact on F–B engagement.

Both theoretical and empirical support for this claim comes from the SI literature (Aral & Walker, 2014), as noted earlier in Section 3.1. Through large-scale in vivo experiments, Aral and Walker (2014) have shown that the *tie strength between two individuals* increases the social influence of one person to the other. Tie strength is defined as "a combination of the amount of time, the emotional intensity, the intimacy, and the reciprocal services which characterize the tie" (Granovetter, 1973, p. 1361). Strong ties are generally measured as *the frequency of dyadic interaction as a proxy* (Bond, Fariss, & Jones, 2012), the relationship category (such as "Follower"), the frequency of information exchange and interactions, and the perceived importance and intimacy of the relationships (Granovetter, 1983). Consequently, frequent interactions and increased social affiliation and intimacy indicate greater influence conducted between individuals connected online (Aral & Walker, 2014).

Recall that Influencers create a sense of friendship, trust, and authenticity among their Followers' perceptions of them (Section 2.1) in their attempt to increase their Followers' engagement with their content (Abidin, 2018; Cotter, 2019). We argue that such a strong bond which Influencers built with their Followers is equivalent to a strong-tie-relationship in SI literature based on the increased intimacy, affiliation, and interactions in Influencer-Follower relationships. As such, Influencers' opinions will matter more for their Followers' decisions on engaging with the brand. Based on the notion of strong ties, we argue that there must be increased social affiliation and frequent interactions between Influencers and their Followers in order for Influencers to induce their Followers' brand engagement, because frequent social interactions are predictive of greater influence. Therefore, we argue:

Hypothesis 3. Followers' engagement with the Influencers' posts will fully mediate the effects of visual congruence on Followers' engagement with the brand's posts.

Table 1
Data collection time periods and purposes.

Time Periods	Datasets collected and purposes
Time Period 1 (T1): 13 months from January 2017 to February 2018	Visual components of the posts that Influencers and their Followers uploaded → to be used for constructing visual congruence Follower engagement behaviors in their Influencers' posts (liking, following and commenting) and other network activity variables → to be used for hypothesis testing
Time Period 2 (T2): 13 months from March 2018 to April 2019	Follower engagement in the target brand's posts (liking, following and commenting) and other network activity variables→ to be used for hypothesis testing The brand's posts (liking, following, commenting and other network activity variables) → to be used for social media analytics

5. Overview of methodology

5.1. Data collection and selection of methods

We collected Instagram data during two time periods (T1 and T2), each of which covers 13 months (a total of 26 months in Table 1). Collecting observations for more than two years allows us to examine how Influencers earn engagement from their Followers, and how they gradually pass positive brand attitudes to their Followers. That is, an observational period of 26 months enables us to capture the long-standing effects that Influencers have on their Followers' brand engagement, whereas a short-term observational period cannot. This long-term investigation suits our interests in Influencers, who build deep relationships with their Followers, and *not* celebrity brand endorsers, who are incentivized by immediate sales increases.

For the data analyses, we employed (1) deep-learning algorithms to automatically classify the visual components of Instagram posts and (2) econometrics modeling to conduct social media analytics (Fig. 2), as noted in Sections 6 and 7, respectively.

5.2. Study context

The brand we chose for this study is Lululemon Athletica (Nasdaq: LULU, Lululemon, henceforth), which specializes in high-end active-wear, especially yoga and fitness apparel. The company reported revenues of 3.3 billion USD in 2018, which represents a 27% growth from 2.6 billion USD in 2017 (Yahoo! Finance). Critiques attribute this substantial growth to the Influencer marketing campaigns known as "Uniting Community in Real Life." This campaign was designed to build, sustain, and expand Lululemon's loyal customer base in local communities. To promote the success of this campaign, Lululemon enlisted yoga/fitness trainers and athletes who are well known in their respective local communities and who have established a social media presence. Lululemon invites them to attend various complimentary training programs and networking opportunities, and acknowledges them with the honorary title of "brand ambassadors" (Mainwaring, 2018). These complimentary events and recognition are intended to nurture loyalty among

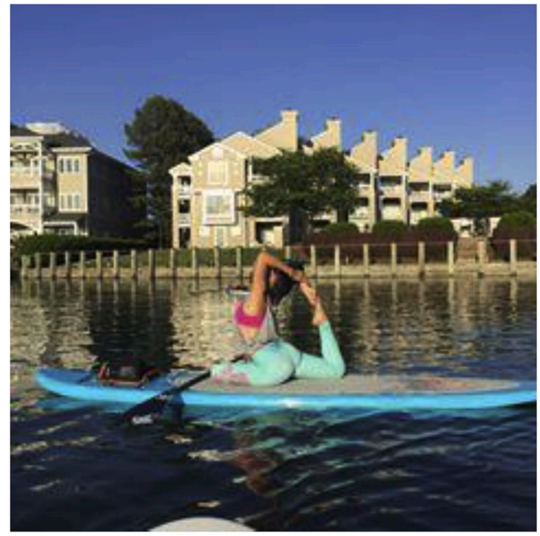

Fig. 3. Influencers' posts naturally integrate Lululemon products due to their brand loyalty. An example of an Influencer's post engaged in physical activity while wearing the brand clothing.

Table 2
Influencers' postings.

Influencer	% of posts with Lululemon hashtag	% of physical activity-themed posts	% of posts showing Lululemon-style clothing	% of physical activity-Themed posts showing Lululemon-style clothing
Mean	3.0%	46%	43%	75%
Std Dv	6.7%	15%	15%	14%

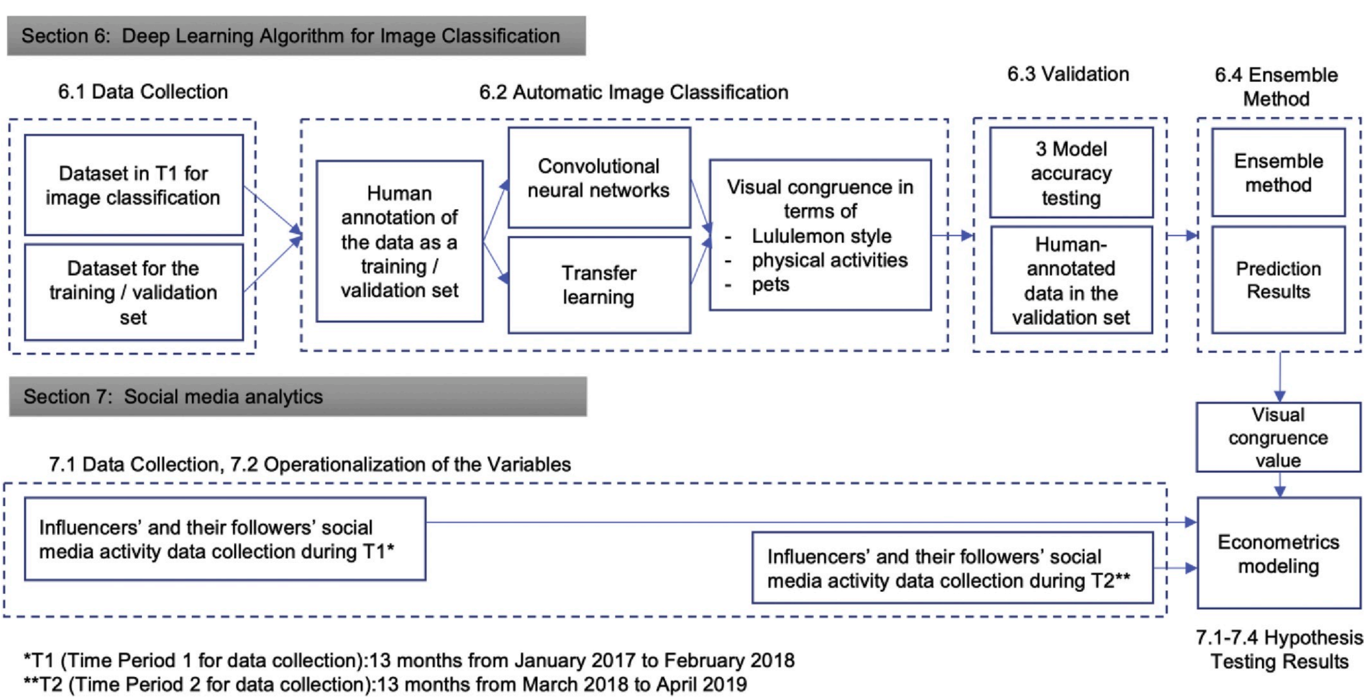

Fig. 2. We combined deep-learning algorithms for image classification with social media analytics to test our hypotheses using a large amount of data collected over two time periods surrounding the real-world Influencer marketing.

the ambassadors, thus resulting in more Lululemon clothing integrated into their daily posts. For instance, they may post pictures of themselves practicing yoga wearing Lululemon clothing (Fig. 3). Since they already have an established social media presence, their wearing Lululemon clothing (even though not accompanied by a direct promotion message) helps create positive brand attitudes among their Followers (Jin & Muqaddam, 2019). As such, we chose these Lululemon brand ambassadors as the *Influencers*.

The data support our choice of Lululemon ambassadors (Table 2). Forty-six percent of Lululemon ambassadors' posts show physical activities (e.g., an ambassador practicing Yoga, Figs. 3), and 43% of their posts contain Lululemon-style clothing. Further, in 75% of their posts showing physical activities, Lululemon ambassadors wear Lululemon-style clothing (as in Fig. 3). However, they do not directly promote the brand, as evidenced by only 3% of their posts containing Lululemon hashtags. As such, Lululemon brand ambassadors demonstrate their expertise in brand-pertinent areas, showcase the brand, and yet, promote the brand indirectly, which closely fits our definition of Influencers. Detailed descriptions of how we classified the visual themes of their images in Section 6.

Followers are those individuals who subscribe to Influencers' posts on Instagram, which provides a feature called "follow" that allows one to receive updates from selected accounts. The difference between "follow" on Facebook and on Instagram is that the former requires approval to receive updates, while the latter does not. Anyone can follow a user's public profile. As user engagement tools, Instagram provides following, liking, and commenting; however, sharing/reposting is not available on Instagram.

6. Deep learning algorithms for image classification

We developed deep-learning algorithms to classify three visual themes—(i) physical activities (to measure visual congruence for hypothesis testing), (ii) Lululemon-style clothing (which was not used for hypothesis testing, but was necessary to confirm that the Lululemon ambassadors featured the brand in their posts in Section 5.2, Table 2), and (iii) pets (which were not used for hypothesis testing, but were used for one of the robustness checks in Section 7.4, wherein detailed justifications for choosing pets are provided).

6.1. Data collection

In T1, we selected Influencers from the list of Lululemon brand ambassadors on the brand's official website. We did not choose profiles with fewer than 2000 Followers at T1 because common practices start with 2000 Followers as the minimum base (Cotter, Cho, & Rader, 2017). In February 2018, there were 110 Influencers with 2000 or more Followers. Of the 110 profiles, we randomly selected 30 accounts for the data analyses, following the principles of probability sampling (Waksberg, 1978). Probability sampling is a fair way to select a sample, and it is reasonable to generalize the results from the sample back to the population (Waksberg, 1978). To ensure that the randomly selected sample represents the population, we adhered to a pre-established procedure (Waksberg, 1978). Specifically, we first created a list of the 110 Influencers on a spreadsheet, assigned a unique ID to each of them, generated 30 random numbers, and chose the Influencers with those numbers.

In the same manner, we next randomly selected 30 Followers per Influencer who had engaged with the Influencer's posts (e.g., liking, commenting) at least once during T1 (13 months). It is widely known that machine-generated Instagram accounts that artificially augment the size of Followers are abound on Instagram (called "ghosts") (Cotter, 2019). To prevent these ghost accounts from affecting our data analyses, we selected only those with a history of interactions with their Influencers in the 13-month period in T1. We looked into our data to see whether these non-likers had the characteristics of "ghost" accounts (Table 3). To do so, we randomly selected 30 non-likers per Influencer (who had never engaged with the Influencers in 13 months). In fact, non-likers follow five-times more accounts than do likers and receive 20 times fewer likes and comments from other users than do likers. These differences support the suspicion in the prior literature regarding non-likers, and thus, we chose likers only. *In summary, our initial sample consisted of 30 Influencers and 900 Followers (30 Influencers * 30 Followers/Influencer).*

Table 3
Comparisons between non-likers and likers.

	Non-Likers	Likers
Out-degree centrality (i.e., the number of Instagram users whom the Follower subscribes to)	8354 accounts	1566 accounts
Number of likes received per post	4.5 likes	94.5 likes
Number of comments received per post	7.7 comments	167 comments

6.1.1. Dataset for image classification and training/validation

From each selected Instagram account, we randomly downloaded 50 images. As such, *we obtained a total of 1500 images of Influencers and 45,000 images of Followers in T1*. To analyze this massive number of images, we adopted a machine-learning approach as follows.

6.1.2. Dataset for training/validation

For training and validation, we separately downloaded 1000 images of physical activity from Influencers, Followers, and benchmark Instagram pages; thus, a total of 3000 images were used. We annotated these images as the next step to train the algorithms in physical activity, Lululemon style, and pets, as shown in Fig. 4. In each category, the training set contains 500 positive samples (i.e., presence of the visual theme of interest) and 500 negative samples (i.e., absence thereof). For model training, in each category, we randomly selected 800 images (400 positive and 400 negative images) to train our models, and the remaining 200 images were used as validation sets. To prevent an overfitting issue, we employed data augmentation to increase the numbers of available training images tenfold. Specifically, the augmentation operations included image rotation, translation, and rescaling, which means that for each original image, the deep-learning framework rotates and/or translates and/or rescales this image to generate 10 copies of it. *Therefore, when developing the training models, there were 8000 training images for each category, with a total of 24,000 images.*

6.2. Automatic image classification

6.2.1. Human annotation of the training set

We hired three coders per image category, for a total of nine coders, to manually annotate the images in the training set. They had demographic factors similar to those of Lululemon's target consumers (females in their 20s) and were active Instagram users. They were thoroughly trained to label images in two 60-min training sessions. During the training sessions, we clearly defined each category, gave them practice questions, and corrected their answers if there were any errors. We did *not* inform them of our hypotheses in order to prevent our expectations from affecting their labeling. Each coder worked on her own to ensure independent coding. We selected the final labels based on the majority-vote rule (2 vs. 1) in the absence of unanimous coding results.

6.2.2. Fine-tuning of the three CNN models

The next step was to fine-tune three deep-learning models to serve our research purposes. We chose to use transfer learning, a type of machine learning that transfers prior knowledge (i.e., learned information) about trained images to a new set of unlabeled images (LeCun & Bengio, 1995). Specifically, we fine-tuned three powerful deep-learning models – VGG 19 (Yosinski, Clune, Bengio, & Lipson, 2014), ResNet 50

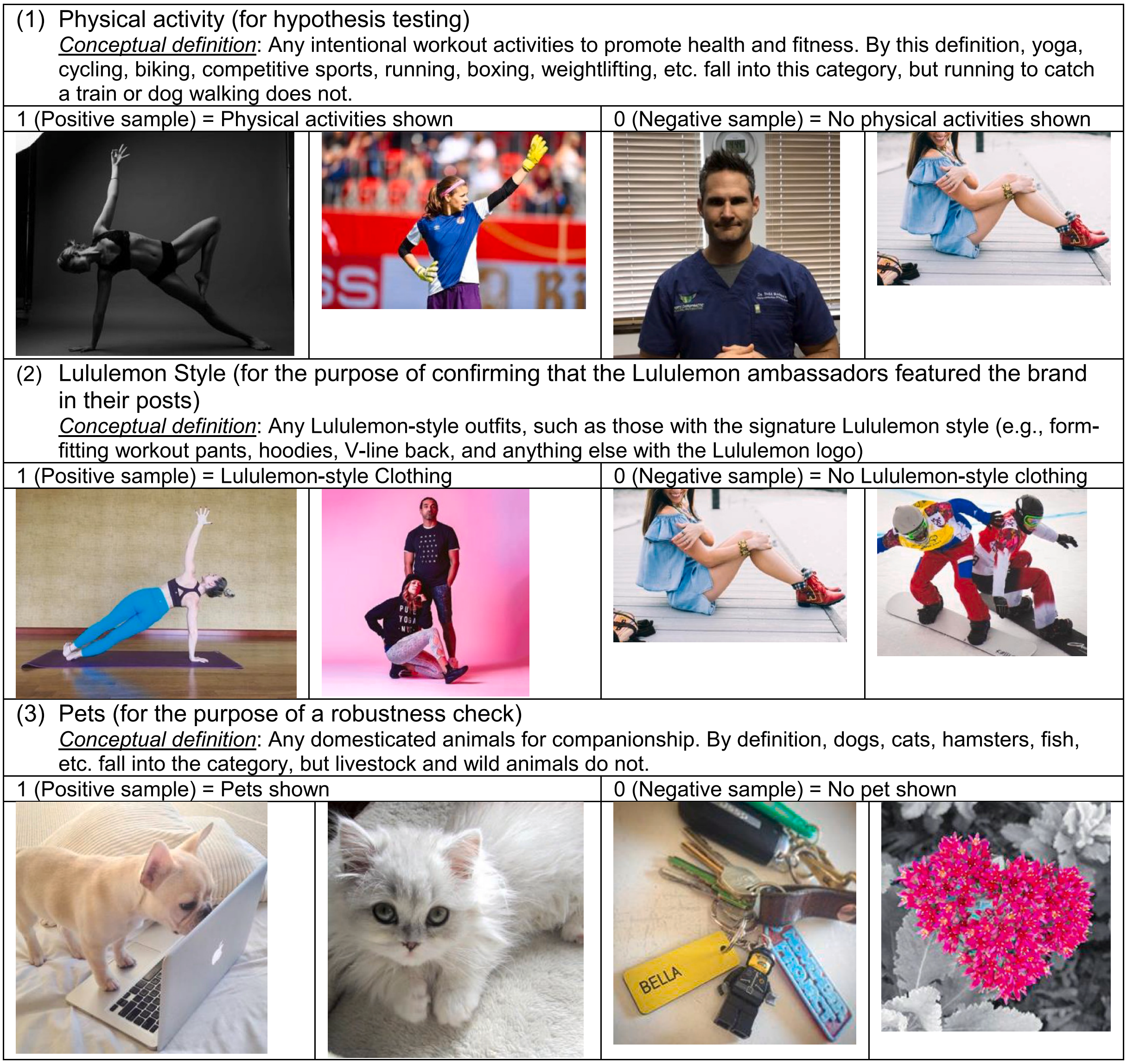

Fig. 4. Definitions of each image feature and examples of image annotation.

(Razavian, Azizpour, Sullivan, & Carlsson, 2014) and Inception V3 (Simonyan & Zisserman, 2014). The VGG19 model won first and second place in the localization and classification tasks in the 2014 ImageNet Large Scale Visual Recognition Competition (ILSVRC) (He et al., 2016). ResNet50 won first place in the classification task in ILSVRC 2015 (Szegedy et al., 2016). The InceptionV3 model demonstrated the lowest error rate in the classification task at ILSVRC 2012 (Szegedy et al., 2016). *The three CNN models have shown robust performance for the types of image classification necessary for our study.*

These three pre-trained models on the ImageNet data were fine-tuned separately with our training set. To obtain the best results, we varied the learning rate from 1e-6 to 1e-4 and chose a training optimizer, Stochastic Gradient Descent (Robbins & Monro, 1951), RMSprop (Graves, 2013), and Adam (Kingma & Ba, 2014). Only the set of hyperparameters that gave the best accuracy rate was used in the model. The final prediction task was conducted as a multilabel classification, with each category (either physical activities or pets) being a binary class. For the three selected models, besides adding one fully connected layer, all of the models were modified to have only one neuron in the final output layer to make predictions. Specifically, in the final output layer, we employed a *sigmoid* function as shown below (Han & Moraga, 1995):

$$s(\boldsymbol{x}) = \frac{1}{1 + e^{-x}}$$

where is the output values of previous layers, and $s(\boldsymbol{x})$is the final model output value that ranges from 0 to 1. When the model completes training, $s(\boldsymbol{x})$is close to 1 for positive samples, and 0 for negative samples. Thus, $s(\boldsymbol{x}) > 0.5$, indicates that an image has the target visual feature; $s(\boldsymbol{x}) \leq 0.5$ suggests the lack thereof.

6.3. Validation

We used the accuracy rate and cross entropy to measure model performance. The accuracy rate reflects the percentage of accurate predictions by the model (calculated as a harmonic function of precision and recall). Cross entropy, whose value ranges from 0 to 1, is a loss function—the lower the number is, the better the model performs. For the training sets, all models perform at almost 100% training accuracy and obtain no more than 0.05% training loss values. Table 4 shows the accuracy testing results for the validation set. *The validation results indicate that the classifiers are accurate and reliable and can provide reliable classifications on our dataset.*

6.4. Ensemble method

Each image was classified by the above three models individually and produced prediction results. To obtain the most reliable classification results, we applied the majority-vote rule. Specifically, if the three models produced unanimous predictions, we accepted them. Otherwise, the values of the two models that produced the same results were averaged to generate the final prediction score ($s(\boldsymbol{x})$), and thus, the classification result.

7. Social media analytics

7.1. Operationalization of the variables

7.1.1. Follower's engagement

We counted the number of times the Follower *liked* or *commented* on the Influencer's posts in T1 as a measure for F–I engagement. Recall that Instagram does not provide sharing or reposting features. In the same vein, we counted the number of times the Follower liked or commented on the brand's posts in T2 as a measure for F–B engagement. The reason we observed F–I engagement in T1 and F–B engagement in T2 is that we wanted to see how F–I induces F–B engagement, while preventing reverse causality.

We ought to note that our conceptualization of followers' engagement refers to the behavioral dimension of consumer brand engagement (CBE) by Brodie, Hollebeek, Jurić, and Ilić (2011). Brodie et al. provided a systematic conceptualization of customer engagement—which entails cognitive, emotional, and behavioral aspects. Cognitive processing concerns a consumer's level of brand-related thought processing and elaboration; emotional dimension (i.e., affection) corresponds to a positive brand-related affect; behavioral dimension (i.e., activation) refers to a consumer's level of energy, effort and time spent on a brand (Hollebeek, Glynn, & Brodie, 2014). The first two dimensions require self-reported measures (e.g., surveys and interviews) which our in-vivo observation of social media behaviors does not involve. Thus, we focused on the observable social media behaviors on Instagram—i.e., liking and commenting—to conceptualize followers' engagement.

7.1.2. Visual congruence

We counted the number of images labeled as physical activity for each Follower and Influencer to calculate the visual congruence value for each Influencer-Follower pair existing in our dataset. Then, we adopted Jaffe's (1986) proximity measure, which was originally designed to calculate the degree of overlap among two actors' research portfolios. The index ranges from zero when there is no overlap (e.g., neither Influencer *i* and Follower *j* has a post pertinent to a target theme) to 1 when there is a complete overlap (i.e., all of Influencer *i's* and Follower *j's* posts contain the same target theme). The visual congruence between Influencer *i* and Follower *j* with respect to a theme in T1 was calculated as follows:

$$\frac{(\#\ \text{of}\ i\text{'s Themed images})*(\#\ \text{of}\ j\text{'s Themed images})}{\sqrt{(\#\ \text{of}\ i\text{'s Themed images})^2+(\#\ \text{of}\ i\text{'s non}-\text{Themed images})^2}*\sqrt{(\#\ \text{of}\ j\text{'s Themed images})^2+(\#\ \text{of}\ i\text{'s non}-\text{Themed images})^2}}$$

7.1.3. Controls

We controlled for several factors that are likely to affect F–I and F–B engagement, as shown in Table 5. Note that, at this stage, we did not include Influencer-specific controls such as the Influencer's posting activity level, engagement with Lululemon's posts, mentions of Lululemon (e.g., hashtag), network centrality (based on the number of Followers and Followees), and the time elapsed since the Influencer became an ambassador. These heterogeneities may exist among Influencers, but they are controlled by Poisson regression estimation with Influencer fixed effects, which we employed for the subsequent analysis (Woodbridge, 2010).

7.2. Model specification and final sample

The unit of analysis is at the Influencer-Follower dyadic level. For the analysis, we employed Poisson regression with Influencer fixed-effect estimation. We chose Poisson regression because the dependent variables, F–I and F–B engagement, are count variables. We chose Influencer fixed-effect estimation to control for the correlations among Followers of the same Influencer, which could interfere with our hypothesis testing. Specifically, some may argue that the Followers of an Influencer are more similar to one another (and thus, are more highly inter-correlated) than the Followers of another Influencer. Fixed-effect estimation

Table 4
Model accuracy testing results.

Models	Datasets	Accuracy	Precision[a]	Specificity[b]	Recall[c]
VGG19	Physical activity	85%	81.8%	88.4%	79.7%
	Lululemon style	85%	86.5%	88.6%	81.1%
	Pet	93%	96.4%	97.2%	88%
ResNet-50	Physical activity	87%	83.5%	89.3%	83.5%
	Lululemon style	89.5%	91.1%	92.4%	86.3%
	Pet	93.5%	97.6%	98.1%	88%
InceptionV3	Physical activity	86%	82.3%	88.4%	82.3%
	Lululemon style	86%	87.6%	89.5%	82.1%
	Pet	95%	97.7%	98.1%	91.3%

[a] Precision (a.k.a. positive predictive value) is the ability of the classifier not to label a sample as positive when it is negative. It is the percentage of relevant instances of all retrieved instances.

[b] Specificity (a.k.a. selectivity, true negative rate) measures the proportion of true negative samples that are correctly classified.

[c] Recall (a.k.a. sensitivity, true positive rate) is the ability of the classifier to find all positive samples. It describes the percentage of retrieved relevant instances over the total relevant instances.

Table 5
Descriptions of control variables.

Variable	Operationalization
Follower's Posting Activity	The number of postings, likes, and comments the Follower generated in T1.
Follower's In-degree Centrality	The number of Instagram users who subscribe to the Follower in T1.
Follower's Out-degree Centrality	The number of Instagram users to whom the Follower subscribes in T1.
Brand Following	Whether the Follower subscribes to the Lululemon account in T1 (Yes = 1, No = 0).
Brand Following (T2)	Whether the Follower subscribes to Lululemon account in T2 (Yes = 1, No = 0). This variable was included to control for those individuals who had had high engagement with the brand to begin with, regardless of their engagement in the Influencers' posts.

controls for such potential similarity (Williams, Petrosky, Hernandez, & Page, 2011). Another advantage is that the estimation is not biased by unobserved Influencer-specific (time-invariant) heterogeneities, such as gender, age, ethnicity, tenure as a Lululemon ambassador, posting activity, and network position, to name a few (Williams et al., 2011). Due to these advantages, we chose the fixed-effect Poisson regression model. Specifically, the fixed-effect Poisson regression of Follower *i*'s engagement with Influencer *j* in T1 is as follows:

$$Follower - Influencer\ \ Engagement_{ij.T1} = \alpha + \beta_1 Visual\ \ Congruence_{ij.T1} + \gamma_1 X_{i.T1} + \alpha_j + \ \ \varepsilon_{ij}$$

where X_i denotes the control variables specific to Follower *i* (described in Table 5) and α_j represents Influencer *j* fixed effects. This model examines the association between visual congruence and F–I engagement in T1.

The fixed-effect Poisson regression model of Follower *i*'s engagement with the brand endorsed by Influencer *j* in T2 is as follows:

$$\begin{aligned} Follower - Brand\ \ Engagement_{ij.T2} &= \alpha + \beta_2 Follower - Influencer\ \ Engagement_{ij.T1} + \beta_3 Visual\ \ Congruence\ \ _{ij.T1} \\ &+ \gamma_2 X_{i.T1/2} + \alpha_j + \varepsilon_{ij} \end{aligned}$$

where X_{ji} denotes the control variables and α_j represents Influencer *j* fixed effects. This model is designed to examine (1) the positive effect of F–I engagement (in T1) on F–B engagement (in T2), and (2) the mediation effect of F–I engagement on the relationship between visual congruence and F–B engagement.

Our initial dataset consisted of 900 observations (30 Influencers and 30 Followers/Influencer). We later found that three Influencers' accounts were closed down in T2, so we decided to eliminate those three Influencers and their Followers from our analysis. For the same reason, we removed three Followers whose accounts were closed in T2. *In the end, our final dataset consisted of 807 observations (27 Influencers and 807 of their Followers).*

7.3. Results

7.3.1. Descriptive statistics

Table 6 provides the descriptive statistics of the 27 Influencers and their Followers in T2.

Influencers and Followers are clearly contrasted in terms of in-degree and out-degree centrality. Influencers have much higher in-degree centrality (13,763 vs. 4,085, which means that they have a lot more Followers), but much lower out-degree centrality (1664 vs. 4,113, which means that they follow a lot fewer people) than their Followers. Third, Influencers' posts included more images, received nearly twice as many *likes* (endorsements), and 42 times more *comments* (responses) than their Followers. *These differences suggest that the ambassadors are likely to exert influence on Followers, and not the other way around* (Hannerman & Riddle, 2005). The descriptive statistics of the brand, Lululemon, are presented in Table 7.

Table 6
Influencer-follower descriptive statistics (in T2 as of April 2019).

	Influencer	Follower
In-degree Centrality (# of Followers)	13,763.4 (11,503.2)	4085.5 (1553.6)
Out-degree Centrality (# of followings)	1664.9 (1505.6)	4113.2 (11,360.4)
Posting Activity		
Image postings in T2	52.4 (85.6)	28.6 (50.3)
Likes received/post	222.1 (489.1)	141.2 (366.4)
Comments received/post	253.2 (124.1)	6.3 (10.8)

Note: Mean (Standard Deviation).

Table 7
Brand descriptive statistics (in T2).

In-degree Centrality (# of Followers)	Out-degree Centrality (# of followings)	# of posts/month	# of likes received/post	# of comments received/post
3 million	170	23.7	241.6 (337.6)	23,086.7 (11,810.2)

As expected, the brand actively engages with consumers on Instagram. It has more than 3 million Followers but follows only 170 accounts. It produces roughly 1 post per business day (23.7 posts/month), receives more than 240 likes/post and more than 23,000 comments/post. Given that the comments indicate higher levels of engagement than likes in social media campaigns (Soltysinska, 2017), these data show that Lululemon has a large and active customer base on Instagram.

Table 8 shows the descriptive statics of the variables, including correlations. Before the analysis, a natural-log transformation was applied to highly skewed variables, such as the number of postings, the number of Followers (out-degree centrality), and the number of Followees (in-degree centrality), as indicated by "(ln)" in the regression result tables (Tables 9–11). The variance inflation factors (VIFs) for all variables were below 2.0, in both of the models explained above, demonstrating that multicollinearity was not a concern in any of the correlations among the variables.

7.3.2. Hypothesis 1 testing results

Table 9 reports the result of the Poisson Influencer fixed-effect regression model of <u>*the Follower's engagement with the Influencer in T1*</u>. Model 1 presents the base model with the control variables only. Model 2 adds visual congruence to the base model. In addition to log likelihood, we report Akaike's information criterion (AIC), which is a measure of goodness-of-fit based on the tradeoff between the complexity and precision of a model (Akaike, 1974). The smaller the AIC value, the better the model is. Model 2 has a better result and shows that the coefficient for visual congruence is positive and significant (0.735, $p < .001$), supporting the notion that visual congruence is positively associated with F–I engagement. Thus, H1, which states that visual congruence is positively associated with Followers' engagement in the Influencers' posts, is supported.

7.3.3. Hypothesis 2 & Hypothesis 3 testing results

Next, we tested both H2 and H3. H2 states that F–I engagement (in T1) will increase F–B engagement (in T2) (i.e., M→Y in Fig. 5). H3 states that visual congruence will increase F–B engagement, and this relationship <u>*is fully mediated by*</u> F–I engagement (i.e., X→M→Y). There are four steps that need to be met in establishing mediation (Baron & Kenny, 1986).

- Step 1: X affects Y in the absence of M.
- Step 2: X is associated with M (H1).
- Step 3: M affects Y in the presence of X (H2).
- Step 4: If X no longer affects Y in the presence of M, and the three conditions above are all met, the X–Y relationship is fully mediated by M (H3).

Table 8
Descriptive Statistics of the Variables (mean, SD, and correlation coefficients).

Variable	Mean	Std Dv	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Follower-Influencer Engagement	10.42	17.82	1							
(2) Follower-Brand Engagement	0.04	0.34	.096*	1						
(3) Congruence - Physical Activities	0.15	0.16	.062	.039	1					
(4) Congruence- Pets	0.00	0.02	-.046	-.016	-.079	1				
(5) Posting Activity*	5684.3	28,416	.010	.051	.081*	-.053	1			
(6) In-degree Centrality*	1494.91	1433	.142***	-.038	-.037	-.046	.137**	1		
(7) Out-degree Centrality*	4100.82	14,116	.060	.032	.150***	-.115**	.409***	.314***	1	
(8) Brand Following (T1)	0.28	0.451	.057	.202***	.178***	-.046	.025	.111**	.032	1
(9) Brand Following (T2)	0.36	0.482	.070	.120**	.164***	-.064	.087*	.148**	.116**	.789***

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 9
H1 testing results.

VARIABLES	(1)	(2)
Posting Activity (ln)	.048***	.047**
	(.005)	(.005)
In-degree Centrality (ln)	.001	-.012
	(.012)	(.011)
Out-degree Centrality (ln)	-.178***	-.174***
	(.009)	(.009)
Brand Following (T1)	.169***	.123***
	(.028)	(.028)
Congruence - Physical Activities		**.735*** **
		(.090)
Influencer Fixed Effects	Yes	Yes
Log Likelihood	−5192.71	−5160.25
AIC	10393.4	10330.9

Note: DV – the Follower's engagement with the Influencer's posts (T1); standard errors are shown in parentheses; ln = Log transformed; **$p < 0.01$, ***$p < 0.001$.

Table 10
H2 & H3 testing results.

VARIABLES	(1)	(2)	(3)
Posting Activity (ln)	.282	.249	.145
	(.178)	(.163)	(.139)
In-degree Centrality (ln)	.381	.391	.373
	(.244)	(.243)	(.227)
Out-degree Centrality (ln)	-.876*	-.830*	-.515
	(.356)	(.353)	(.373)
Brand Following (T2)	1.268*	1.09*	.970
	(.514)	(.523)	(.527)
Congruence - Physical Activities		.444*	.385
		(.200)	(.238)
Engagement with the Influencer			.504**
			(.184)
Influencer Fixed Effects	Yes	Yes	Yes
Log Likelihood	−70.21	−68.61	−64.54
AIC	148.42	147.22	141.07

Note: DV – the Follower's engagement with Lululemon's posts (T2); standard errors are shown in parentheses; ln = Log transformed; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

The empirical support for H1 (Table 9) means that Step 2 is met. Table 10 reports the result of the Poisson Influencer Fixed-effect regression model of F–B engagement (Y). Table 10 shows that the remaining three steps are all satisfied in our model estimation. Model 1 presents the base model with the control variables only. Model 2 tests Step 1 by adding visual congruence (X) to the base model. In Model 2, the coefficient for visual congruence is positive and significant (0.444, $p < .005$), thus satisfying Step 1. Model 3 adds F–I engagement (M) to Model 2. In Model 3, the coefficient for F–I engagement (M) is positive and significant (0.504, $p < .01$), supporting Step 3 as well as H2, such that F–I engagement will increase F–B engagement. In addition, the coefficient for visual congruence (X) becomes non-significant (0.385, *n. s.*) once F–I engagement (M) is added to the model. The results indicate that the positive effect of visual congruence on F–B engagement is fully mediated by F–I engagement, supporting H3.

Table 11
Robustness test results for H1 (T1).

VARIABLES	(1) Combination Approach	(2) Continuing Followers Only	(3) Unfollowers Only (T2)	(4) Pets added
Posting Activity (ln)	.048***	.048***	.064***	.046***
	(.005)	(.005)	(.015)	(.005)
In-degree Centrality (ln)	-.011	.111***	.014	-.018
	(.012)	(.014)	(.031)	(.012)
Out-degree Centrality (ln)	-.175***	-.546***	-.505***	-.176***
	(.009)	(.223)	(.045)	(.009)
Brand Following (T1)	.130***	.199***	-.064	.117***
	(.028)	(.032)	(.091)	(.028)
Congruence - Physical Activities (T1)	.630***	.513***	.205	.709***
	(.093)	(.100)	(.320)	(.091)
Congruence - Pets				-.077
				(.020)
Influencer Fixed Effects	Yes	Yes	Yes	Yes
Log Likelihood	−5169.92	−3909.20	−733.78	−5141.47
AIC	10349.38	7827.658	1477.56	10296.94

Note: DV – the Follower's engagement in the Influencer's posts (T1); standard errors are shown in parentheses; ln = Log transformed; **$p < 0.01$, ***$p < 0.001$.

7.4. Robustness checks

We took several alternative approaches to test the robustness of the results. Table 11 reports the robustness test results for F–I engagement (H1), and Table 12 reports the robustness test results for F–B engagement (H2 and H3).

First, we used an alternative measure of visual congruence. Recall that when predicting image themes, we followed the majority-vote rule, as explained in **Section 6.4, Ensemble Method**. Instead of relying on the majority-vote, we averaged the values of the three models to produce the final prediction scores. Model 1 in Tables 11 and 12 report the results. The results in both models remain unchanged, meaning that *the majority-vote rule is reliable*.

Second, we ran another robustness check for our mediation analysis. There were some Followers who chose to "unfollow" their Influencers in T2 (N = 193), and we believe that these Unfollowers' brand engagement in T2 should NOT be affected by the visual congruence with their Influencers in T1, if F–I engagement is a necessary condition for visual congruence to induce brand engagement (H3). We thus ran a split test—dividing the Followers into two groups (continuing Followers only vs. Unfollowers only). Model 2 in Tables 11 and 12 reports the results for continuing Followers only, and Model 3 reports the results for

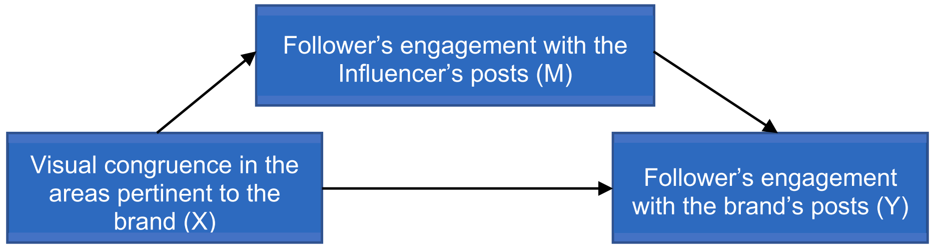

Fig. 5. Hypothesized mediation effects.

Table 12
Robustness test results for H2 & H3.

VARIABLES	(1) Combination Approach		(2) Continuing Followers Only		(4) Pets added	
Posting Activity (ln)	.252	.146	.098	.053	.252	.145
	(.164)	(.140)	(.109)	(.109)	(.164)	(.139)
In-degree Centrality (ln)	.403	.383	.306	.243	.402	.383
	(.245)	(.228)	(.247)	(.245)	(.250)	(.229)
Out-degree Centrality (ln)	-.854*	-.535	-.862*	-.639	-.854*	-.535
	(.352)	(.371)	(.379)	(.402)	(.351)	(.372)
Brand Following (T2)	1.10*	.968	.908	.888	1.10*	.968
	(.523)	(.527)	(.567)	(.569)	(.523)	(.527)
Congruence - Physical Activities	.473*	.415	.209ƚ	.202	.472*	.416
	(.224)	(.243)	(.107)	(.295)	(.245)	(.234)
Engagement with the Influencer		.504**		.343ƚ		.504**
		(.185)		(206)		(.185)
Congruence - Pets					-.028	.008
					(.334)	(.320)
Influencer Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	−68.47	−64.41	−51.70	−50.26	−68.46	−64.41
AIC	146.94	140.82	113.41	112.53	148.93	142.82

Note: DV – the Follower's engagement with Lululemon's posts (T2); standard errors are shown in parentheses; ln = Log transformed; ƚ $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Unfollowers only. The results remain unchanged in the case of continuing Followers (Model 2), whereas we found no support for visual congruence on the Unfollowers' brand engagement. We could not even obtain the results for Unfollowers' engagement with the brand because there is no instance where Unfollowers engage with the brand postings in T2. Thus, no further steps could be taken for a mediation analysis. In short, when Followers discontinue engaging with their Influencers, they no longer engage with the brand, regardless of the extent of visual congruence with their Influencers. *These robustness check results render further* support *for our mediation analysis.*

Third, *we maintain that Influencers' visual congruence with their Followers should be built in areas that are pertinent to the brand.* We tested whether visual congruence based on a brand-*unrelated* theme would also increase F–I or F–B engagement. As we briefly mentioned in Section 6, we chose pets as a visual theme, which is irrelevant to Lululemon. Perceptions about and emotions toward pets are not relevant to the brand, Lululemon. However, shared affection toward pets can serve as strong grounds for building bonds between individuals (Wood et al., 2015). Therefore, pets are good candidates for building visual congruence between Influencers and Followers. Nevertheless, because this pet-based visual congruence is not pertinent to the brand, it should not increase brand engagement. Model 4 in Tables 11 and 12 shows that the coefficient for pet-based visual congruence is not significant, *thus* supporting *our claim.*

8. Discussion and conclusions

8.1. Summary of the findings

Influencer marketing is growing rapidly, especially among millennials, who have become the largest purchasing age group in 2019. Nonetheless, academic research has not yet fully explicated how Influencers garner their Followers' brand engagement. As such, we have maintained that visual congruence, which is manifested in Influencers' posts to accentuate shared interests with their Followers, is positively associated with increases in Followers' engagement with Influencers, based on SAM. This increased engagement in turn leads to higher brand engagement due to the increased familiarity of the brand and the transference of credibility from Influencers to the brand. Contextualizing SAM to the SI literature, we have also hypothesized that increased F–I engagement fully mediates the relationship between visual congruence and F–B engagement. That is, increased visual congruence suffices for attracting Followers to Influencers, but does not foster Followers' engagement with the brand unless Influencers make continuous efforts to maintain frequent interactions with their Followers.

To test these hypotheses, we employed social media analytics, combined with three open-source CNN models. We collected over 26 months of Lululemon Influencers' and their Followers' Instagram posts (>45,000 images) and social media usage behaviors. We used a training set of 24,000 images (containing both positive and negative samples) to fine-tune three CNN models (VCG19, ResNet-50, and InceptionV3) to fit our data samples. All of the trained models demonstrated acceptable levels of accuracy (>80%) in terms of precision, specificity, and recall. We used an ensemble method to integrate the prediction results from these three models to generate robust results. These automatically classified themes of images were used to calculate the visual congruence between an Influencer-Follower pair, using Jaffe's proximity measure. Our fixed-effect Poisson regression results supported all of our expectations. Our three additional tests involving alternative specifications show that our hypothesis testing results are robust.

8.2. Contributions and implications

This study advances the current literature on social media marketing. We propose a new conceptual framework, VCSI, that contextualizes SAM to SI. This new framework expands SAM by incorporating multimodal elements of social media posts and by delineating the processes by which Influencers affect their Followers' brand engagement. Thus, this study not only applies SAM, but also expands its boundary conditions to newly growing and important areas of visual content. We have also provided systematic and in vivo observations regarding the effectiveness of Influencers to increase brand engagement among large crowds. This rare real-world data collection and these observations warrant adequate empirical grounds for advancing theories in VCSI.

We not only applied deep-learning algorithms for image classification, but also proposed an ensemble method as a robust approach to aid future researchers in their attempts to analyze visual content shared on social media. In addition, we collected a large amount of data over 26 months and used social media analytics to find hidden associations among visual congruence and Followers' engagement with their Influencers and the endorsed brand. We believe that the importance of such combined methods will increase, given the growth of multimodal posts and the availability of large amounts of social media data.

This study also provides many implications for practitioners. Firstly, our results support the widely recognized notion that "a picture is worth 1000 words." Specifically, our major findings indicate that "visual congruence" harnesses followers' engagement. Thus, influencers should carefully analyze and identify the prominent visual features shared by their target audiences. In our study, the visual congruence was built on physical activities, which is the common interest among followers and is pertinent to the brand. This result indicates that visual presentation of the shared themes may be equally, if not more, effective as verbally describing them. Images are recognized more quickly, remembered longer, and engender greater persuasive outcomes than text (Seo, Dillard, & Shen, 2013; Sontag, 2018; Townsend & Kahn, 2013). On Instagram and other rapidly growing platforms for photo-sharing, interactions occur in visual forms (e.g., exchanging images and graphical image files) more so than in textual narratives. Thus, influencers are encouraged to recognize that images can also create substantial social influence for message recipients on social media, as manifested by increased followers' engagement in our study.

Our result on visual congruence also suggests that influencers should not try to distinguish themselves in their attempt to draw more attention to their account but should instead attempt to appear similar to their followers (i.e., "I am one of you" or "I am your friendly neighbor"). In a traditional marketing campaign, the goal is often to distinguish the celebrity model to demonstrate the superiority and uniqueness of the brand. In contrast, the goal of an influencer marketing campaign should be to demonstrate the influencer's familiarity and authenticity (i.e., "realness"). In doing so, their followers, who are weary of celebrity modelled campaigns, can identify themselves with and build deeper connections with the influencer.

Furthermore, one of the major findings of this study is that the brand connection becomes stronger when followers are engaged with the influencer's posts. Firms should thus encourage influencers to identify ways in which they can increase the intimacy and affiliation perceived by their followers. Influencers should make efforts to facilitate interactions with their followers so that they can garner more likes and comments. During the process of actively endorsing the influencers' posts, followers will start internalizing the influencers' affinity toward the brand; the followers' brand engagement will naturally ensue. In order to do this, influencers should diligently respond to incoming comments. Moreover, given how Instagram's content-ranking algorithms prioritize recent posts in search results (Constine, 2018), influencers should identify the time at which the majority of their followers visit their Instagram pages and post their content at these prime times to harvest more likes and comments.

With these implications established, brand managers must recognize that successful influencer marketing campaigns require dedicated influencers who are active in both strategically crafting images and in facilitating interactions with their followers. The followers' brand engagement can then be induced through frequent interactions.

8.3. Limitations of the study and suggestions for future research

As with any study, our research has certain limitations. First, our random sampling of Influencers, Followers, and their images may be limited in representing the population. Given the sheer number of pictures posted by a large number of Influencers and Followers, a sampling method was necessary. We followed the probability sampling technique (Waksberg, 1978), and the data support our conceptualization of Influencers, Followers, and Influencer-marketing campaigns (Tables 2, 6 and 7). Thus, we cautiously argue that our sampling procedure did not interfere with our hypothesis testing. Second, we had a simple temporal separation between T1 and T2 to examine the mediated causal direction from visual congruence to F–B engagement. Using panel data with multiple observation periods would have strengthened causality. Nevertheless, the full mediation of the Followers' engagement with the Influencer provides support for the directionality. Lastly, our conceptualization of followers' engagement included only the behavioral dimension by Hollebeek et al. (2014), given the limitations of in-vivo observations of social media behaviors which do not permit the collection of self-reported measures.

Future researchers are encouraged to overcome the aforementioned limitations in our study. Specifically, researchers may want to employ a panel of Influencers and their Followers and track the interactions between them longitudinally in order to enhance the causal mechanisms underlying Influencers' ability to induce brand engagement among their Followers. Simultaneously, researchers may want to analyze the costs and benefits of such longitudinal data collection from a panel and compare them with those of retrospective data collection over the same length of time (as done in our study). Granted, the use of a panel in a longitudinal study enhances the rigor, but given the advancement of technologies and analytical tools, researchers may be able to obtain equivalent results with alternative methods. Timely empirical observations are becoming ever more important due to rapid technological growth and subsequent changes in society and in our daily lives. Thus, we also encourage researchers to develop a methodology that takes advantage of new, cost-efficient analytical tools without compromising the rigor of their academic investigations. Lastly, researchers may want to investigate other modalities of social media posts that are growing rapidly, in addition to the visual images we explored in this study. Such new modalities include augmented/virtual reality technologies, which are currently available on most social media platforms. Researchers may want to investigate how such new modalities of social media posts increase tie strength, and thus generate social influence.

Declaration of competing interest

Authors have no conflict of interest to report.

CRediT authorship contribution statement

Young Anna Argyris: Conceptualization, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration. **Zuhui Wang:** Methodology, Investigation, Software, Validation, Data curation, Writing - original draft. **Yongsuk Kim:** Methodology, Formal analysis, Writing - original draft. **Zhaozheng Yin:** Methodology, Supervision, Resources, Funding acquisition.

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