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I DON'T NEED A DEGREE, I'VE GOT ABS: INFLUENCER WARMTH AND COMPETENCE, COMMUNICATION MODE, AND STAKEHOLDER ENGAGEMENT ON SOCIAL MEDIA

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In this study we consider whether (a) image- and word-based communication modes and (b) warmth and competence cues vary in their relative influence on different levels of stakeholder engagement on social media. Specifically, we explore social media fitness influencers' abilities to attract followers and get followers to positively interact with them via posts and comments. We theorize that differences in the ways each communication mode is processed, and differences in how competence and warmth cues are perceived, will lead to different relative effects on lower- and higher-engagement behaviors. Using the social media platform Instagram, we followed 488 social media entrepreneurs in the fitness and nutrition industry for six months, and found that images have a positive relationship with less cognitively effortful engagement (following) whereas words do not have a significant relationship, and words have a stronger relationship than images with more cognitively effortful engagement (positive interactions). We also found that competence cues have a stronger positive relationship than warmth cues with the number of followers, and warmth cues have a positive relationship with positive interactions, whereas competence cues do not. Our findings have implications for research on multimodal communication, social judgments, and entrepreneur–stakeholder engagement.

> The first thing I did to become a fitness influencer was open an Instagram account. And that was also the only thing I needed to do to become a reputable fitness influencer … I don't need a degree from a university I was too dumb to get into. I've got abs.
>
> —Social media entrepreneur's fitness influencer parody video

A central challenge all entrepreneurs face is reducing stakeholders' uncertainties so that entrepreneurs can access the resources they need to survive and grow (Stinchcombe, 1965). Entrepreneurs must figure out how to persuade stakeholders that they are competent, trustworthy, moral, and have the stakeholders' interests at heart, so that they will engage with the entrepreneur. Scholars have traditionally focused on how entrepreneurs signal their *competence* through cues such as certifications and affiliations that signal their otherwise unobservable capabilities and expertise to stakeholders (e.g., Nagy, Pollack, Rutherford, & Lohrke, 2012; Petkova, 2012; Plummer, Allison, & Connelly, 2016), but have focused less attention on how they convey their trustworthiness and morality—what psychologists refer to as *warmth* (Fiske, Cuddy, & Glick, 2007). Decades of psychology research has demonstrated that "perceived warmth and competence are the two universal dimensions of human social cognition" (Fiske et al., 2007: 77) that shape social judgments.

The advent of social media has created expectations that entrepreneurs will engage regularly with stakeholders (Fischer & Reuber, 2011) in a noisy and

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highly emotional environment (Dobele, Lindgreen, Beverland, Vanhamme, & van Wijk, 2007; Etter, Ravasi, & Colleoni, 2019) where information is less verifiable and diffuses quickly (Veil, Sellnow, & Petrun, 2012). Social media allows entrepreneurs to communicate directly with their "followers," building emotional connections with them by sharing images, telling stories about themselves (Garud, Gehman, & Giuliani, 2014), and responding to individual followers' comments. Thus, social media puts a great premium on entrepreneurs' abilities to convey the warmth and trustworthiness that makes them likable and worth engaging with (Abele & Wojciszke, 2014; Fiske et al., 2007). By interacting with others on social media platforms, influencers build online communities (Fisher, 2019) and establish credibility that directly influences others' attitudes, beliefs, and buying behaviors (Langner, Hennigs, & Wiedmann, 2013). Social media's contextual differences create new opportunities to theorize how warmth and competence cues affect stakeholders' engagement (van Doorn et al., 2010), and to explore how such cues vary across different kinds of behaviors.

Further, because it is a visual as well as textual medium, social media employs "multimodal" communication, combining images and words to influence others' actions (Barberá-Tomás, Castelló, De Bakker, & Zietsma, 2019; Messaris, 1997; Meyer, Jancsary, Höllerer, & Boxenbaum, 2018). Research on multimodal communication has tended to focus on how differences in semiotics (how symbols relate to meanings), cognitive processes (e.g., comprehension, storage, recall, and associative memory), and contextual features lead images and words to have different effects (Messaris, 1997; Meyer et al., 2018). However, limited research has explored the relative effects of these communication modes (images vs. words) and communication content (competence vs. warmth) on motivating behaviors that vary in their cognitive effort. Separating the influences of communication content and mode is important for understanding how each influences behavior, and how these influences vary across behaviors. Failing to understand which communication modes and content are most effective in stimulating different types of engagement can make online actors' communications less effective than hoped.

In this study we ask the questions: (a) Do images and words vary in their relative influence on stimulating different levels of stakeholder engagement? and (b) Do warmth and competence cues vary in their relative influence on these outcomes? We argue that social media entrepreneurs leverage both images and words that convey their warmth and competence to persuade stakeholders to engage with them at two different engagement levels: (a) following their social media feeds, and (b) engaging in direct positive interactions with their posts. We extend research showing that words and images are processed differently (Hsee, 1998; Messaris, 1997; Meyer et al., 2018; Thorpe, Fize, & Marlot, 1996) to argue that communication modes vary in their relative influence on the different engagement levels. We further argue that communication content also influences the amount of cognitive effort stakeholders exert in their engagement. We suggest that images and competence cues have a greater ability than words and warmth cues to increase lower-level engagement, and that words and warmth cues have a greater influence than images and competence cues on higher-level engagement.

We followed 488 social media entrepreneurs in the fitness and nutrition industry on Instagram for six months to assess how warmth and competence cues, communicated through images and words, influenced the number of followers they have and the extent to which followers positively interacted with them. The fitness industry has no governing body; thus, anyone can claim to be a fitness trainer, and many without formal credentials—but with "killer abs"—use social media platforms like Instagram to attract clients and build their businesses (Melton, Katula, & Mustian, 2008). We found general support for the pattern of relationships we expected, although some effect sizes were not significantly different. We also found that competence images had the largest effect on lower-level engagement, and warmth words had the largest effect on higher-level engagement.

Our study contributes to the literatures on multimodal communication, social judgments, and stakeholder engagement. Multimodal research has often conflated communication mode and content, and traditionally considered how images attract attention and generate strong, often negative, emotions to guide behavior without regard to the cognitive effort the behavior requires (Barberá-Tomás et al., 2019; Jarvis, Goodrick, & Hudson, 2019). We contribute to the literature on multimodal communication by separating content and mode effects, instead comparing the relative effects of images and words that generate positive emotions on lower- and higher-level engagement behaviors. We show that a mode's effectiveness in encouraging a particular engagement behavior depends on the cognitive effort the behavior requires. Whereas images positively influence both lower-level and higher-level engagement behaviors, their relative influence compared to words is greater on lower-level engagement behaviors, because they stimulate positive reactions with less cognitive effort. Thus, we provide insights into how communication modes can vary in encouraging different stakeholder engagement behaviors.

Further, we contribute to the social judgment literature by theorizing how the nature of the actions considered affects warmth and competence cues' relative influence. Whereas research has traditionally found that warmth cues have a greater influence than competence cues (Abele & Wojciszke, 2014; Cuddy et al., 2011), we show that competence cues have a larger relative effect on less cognitively effortful engagement, and warmth cues have a positive relationship with more cognitively effortful engagement, whereas competence does not have a significant relationship.

Finally, we contribute to the literature on entrepreneur–stakeholder engagement, which has typically focused on one-to-one dyadic interactions (e.g., Cardador & Pratt, 2018) in offline contexts, by illustrating that there are differences in dyadic and one-to-many interactions, and examining how different modes and cues can influence stakeholders' engagement with entrepreneurs in the online world.

SOCIAL MEDIA CONTEXT

As social media's popularity has risen, so has the prevalence of social media entrepreneurs known as influencers. Influencers are individuals who leverage social media to sell products and services (Cha, Haddadi, Benevenuto, & Gummadi, 2010). They create businesses by interacting with consumers on social media platforms rather than in person, encouraging them to consume the social media content they generate, and purchase or use products and services they provide or endorse. Thus, they do not primarily use their online presence to advertise or promote their brick-and-mortar businesses; influencers' businesses are primarily—and often wholly—online. Further, unlike journalists in traditional media, social media users are not required to ensure the accuracy of the information they provide (Veil et al., 2012). This means that influencers can disseminate their content and information more easily, using emotions to generate buzz (Dobele et al., 2007; Etter et al., 2019), which creates a greater likelihood that the content they share will influence their followers' judgments about a particular product, service, or brand (Veil et al., 2012).

We focus on two social media user behaviors that are important to influencers' success, and reflect different levels of user engagement with influencers (Ashley & Tuten, 2015; van Doorn et al., 2010). Engagement is the "behavioral manifestations that have a brand or firm focus, beyond purchase, resulting from motivational drivers" (van Doorn et al., 2010: 254). Customers are driven to engage in these behaviors by several factors, such as the desire to socialize with others (Tuškej, Golob, & Podnar, 2013), cocreate content they want to see (Alves, Fernandes, & Raposo, 2016), experience things they normally cannot (Gummerus, Liljander, Weman, & Pihlström, 2012), or share positive and negative feelings (van Doorn et al., 2010).

As argued by van Doorn and colleagues (2010), various customer characteristics affect their engagement level, including their affective state; attitudinal factors such as satisfaction, trust, commitment, and attachment; and their goals (e.g., consumption or relational benefits). These customer characteristics can affect their cognitive processes and decision-making in ways that lead to engagement behaviors varying in their valence (positive or negative); modality or form; scope (e.g., time spent); and immediacy, intensity, breadth, and longevity of impact; as well as in the customer's purpose. For example, positive behaviors that require little time or customer involvement—like reading a post or watching a video—reflect more passive, lower-level engagement; in contrast, more active behaviors that reflect higher-level engagement—such as responding to others' posts or resharing posts with others—involve more direct interaction, time, and involvement on the customer's behalf, and can have significant or longer-term consequences (Ashley & Tuten, 2015; Hutton & Fosdick, 2011). Stimulating customers in different ways can thus lead to engagement behaviors that vary in their intensity, or level.

We consider two social media user behaviors that vary in their engagement level, and are important to influencers. The first, lower-level engagement behavior is choosing to follow the influencer. Following an influencer requires only the time and effort needed to click the "follow" option. Social media users follow individuals for any number of reasons (e.g., to hear about new products, to join a group or feel less lonely, to live vicariously through others) (Croes & Bartels, 2021; Lee, Sudarshan, Sussman, Bright, & Eastin, 2022); however, it is generally because they are interested in seeing the influencer's posts (Ki, Cuevas, Chong, & Lim, 2020), even if they are not motivated to interact more actively with the influencer.

While following is a low-level engagement behavior, followers are a key resource for influencers in the social media context (Forsey, 2020). Attracting more followers gives influencers access to social media platform features that allow them to gain better placement in their followers' feeds (Milan, 2015), obtain brand endorsements and product placements (Jin, Muqaddam, & Ryu, 2019), generate networking opportunities (Krishen, Berezan, Agarwal, & Kachroo, 2016), and access other revenue streams (Tang, Gu, & Whinston, 2012). Thus, having more followers enhances influencers' abilities to shape others' decision-making processes and increase their own revenue opportunities.

Further, the number of followers plays a direct role in social media platforms' algorithms that determine which individuals, and their associated posts, are displayed on users' content feeds (Bojko, 2021). Social media platforms use machine learning algorithms to encourage more targeted and personalized experiences for users (Barnhart, 2021). When users post more frequently, engage with others through commenting on or liking posts, or even just follow new people, the algorithm shifts and adapts to ensure the posts that show up on their feed are ones that they will be more likely to engage with in the future (Luna, 2021). Thus, a key action that influencers can persuade social media users to take is to follow them on social media.

Once they begin following the influencer, the second, higher-level engagement behavior social media users can pursue is positively interacting with the influencer. Positive interaction reflects greater engagement than following because the follower takes the time and effort to reply to or comment on the influencer's posts (van Doorn et al., 2010). Positively interacting with influencers can create online communities that "facilitate communication and exchange among individuals and entities with shared interests" (Fisher, 2019: 279). For the influencer, positive interaction fulfills two purposes. First, positive interaction helps influencers build "relational advantages" (Fisher, 2019: 280) that decrease uncertainty, enabling a sense of trust (Autio, Dahlander, & Frederiksen, 2013) that can lead followers to purchase their products and services, or the products and services they recommend (Loureiro, Serra, & Guerreiro, 2019).

Second, interactions are an important factor in the algorithms social media platforms use to determine the visibility of influencers' posts in users' feeds (Barnhart, 2021). This is because observing an influencer interacting positively with their followers can also attract more followers. Thus, social media influencers regularly reply to their followers' comments, and try to get their followers to engage with and respond to their posts and comments (Cooper, 2019). The more influencers interact with followers, the more the algorithm assumes others will want to see their posts, and the more prominently they are displayed (Barnhart, 2021). For the follower, positively interacting with the influencer can make them feel like they are part of a community (Fisher, 2019), and that they have a relationship with, or connection to, the influencer (Croes & Bartels, 2021; Lee et al., 2022), which aligns with the motivational drivers (e.g., trust, liking, relational goals) underlying higher-level engagement behaviors (Gummerus et al., 2012).

In developing our hypotheses, we argue that different communication modes and communication content will vary in their relative effects on spurring lower and higher levels of engagement. We first focus on how the communication mode is likely to influence each type of engagement, irrespective of the messages' content. We then develop hypotheses about the relative influence of warmth and competence cues on engagement, irrespective of mode.

THEORY AND HYPOTHESIS DEVELOPMENT

Multimodal Communication

Organizations routinely use multiple communication modes—particularly words and images—to convey their messages and persuade stakeholders to adopt certain perspectives and take particular actions (Messaris, 1997; Meyer et al., 2018). For example, Barberá-Tomás and colleagues (2019) studied how social entrepreneurs attempted to reduce plastic pollution in the ocean by getting consumers to use less single-use plastic, rather than just encouraging them to recycle. They argued these social entrepreneurs used "visual images to evoke strong negative emotions of moral shock—including rage, sadness, and despair—among targeted actors to draw attention" and then transformed and directed these "strong emotions into emotional energy that fueled their targets' enactment of the social entrepreneurs' cause" through words (Barberá-Tomás et al., 2019: 1790). Indeed, using images to generate strong, negative emotions and words to frame interpretations and harness their energy has received significant attention (e.g., Barberá-Tomás et al., 2019; Jarvis et al., 2019).

Multimodal communication scholars have focused primarily on images that evoke strong emotional responses (Joffe, 2008; Messaris, 1997), and contexts where the cumulative influence of multiple cues are processed using the same, affective information processing system (e.g., Barberá-Tomás et al., 2019; Jarvis et al., 2019). These images—such as photos of dead albatross chicks (Barberá-Tomás et al., 2019), a dead Syrian child (Fehrenbach & Rodogno, 2015) or abused animals (Jarvis et al., 2019)—evoke strong, often negative, emotional responses. We focus instead on positive images that convey warmth, and images that convey competence. In addition, although prior research has explored how different modes are associated with different behaviors (e.g., that images can attract attention and words can motivate subsequent action), it has given less attention to how different information modes can vary in their relative effects based on the cognitive effort the different behaviors require. We argue that images and words will have different relative effects on lower- and higher-level engagement due to the semiotic and syntactic differences that shape how individuals process information provided through each mode.

The Relative Effects of Communication Modes on Different Levels of Engagement

Messaris (1997: viii) argued that

> Any mode of communication can be described in terms of either semantic or syntactic properties. A semantically oriented description focuses on how elements of a particular mode (e.g., images, words, musical tones) are related to their meanings. A syntactically oriented description is concerned with the interrelationships among the elements themselves as they combine to form larger meaningful units.

Messaris (1997) identified two semantic and one syntactic category that distinguish images and words: iconicity (their ability to resemble the things they represent), indexicality (their ability to document or provide proof that something exists, or has happened), and syntactic determinacy (their ability to convey the nature of relationships among things). Messaris (1997) argued that iconicity and indexicality are prominent features of images, because even basic images such as lines on maps can accurately represent real-world objects, and images such as photos and videos provide documentary evidence that something exists or has occurred. In contrast, iconicity is only a minor feature of text (e.g., onomatopoeia), and indexicality is totally absent.

With respect to syntax, Messaris (1997) argued that in contrast to words, which have clear syntactic rules for establishing meaning, images lack a syntax for identifying how they relate to each other. That is, although associations between images can be implied, images cannot express explicit comparative, causal, or other relationships. The "lack of a clear visual 'syntax' makes visual meaning fluid and indeterminate and strongly dependent on the viewers' interpretational predispositions" (Meyer et al., 2018: 396); that is, it makes it easier for them to see what they want to see. However, this syntactic indeterminacy, far from being a weakness, can be a powerful means of influence, since observers nonetheless make associations, even if they are not explicitly stated (Messaris, 1997). Indeed, syntactic indeterminacy is why celebrities are hired to hawk all manner of products, and political ads employ images that resonate with particular audiences—to create strong, subliminal associations in observers' minds that influence their behaviors (i.e., buying the product or voting for the candidate). Thus, images have iconicity, indexicality, and syntactic indeterminacy, whereas words have syntactic determinacy and some iconicity, but lack indexicality.

Images and words are also processed differently. Research has shown that images are processed more quickly than words (Thorpe et al., 1996), and in a more unmediated fashion, "because viewers are not generally provoked to reflect on or deconstruct them in the way that occurs in relation to verbal material" (Joffe, 2008: 85), making them more salient and vivid (Joffe, 2008; Messaris, 1997). And images can have higher "evaluability" (Finucane et al., 2003; Hsee, 1998)—that is, the degree to which "the judgment is influenced more by attributes that are easy to evaluate than by attributes that are hard to evaluate, even if the hard-to-evaluate attributes are more important" (Hsee, 1998: 109)—because they resemble the things they represent (i.e., iconicity). Observers can therefore assess them using direct comparisons—to others, or to their own experiences and impressions—providing "proof" that gives images greater weight when making assessments (Messaris, 1997).

Words, in contrast, are symbols that can represent abstract concepts. They take longer to process, and are less influential on associative memory and recall compared to images (Baadte & Meinhardt-Injac, 2019). Words are also processed sequentially and linearly, and are less likely to allow for multiple interpretations (Meyer et al., 2018). Thus, words have the capacity to present arguments, make causal connections and indicate temporal and other relationships. They can also stimulate imagery and associated emotions in readers' minds (Paivio, 1991). These differences shape how information presented through different communication modes persuade their recipients to act—and, as we will argue, they also affect the extent to which a particular communication mode is more effective in encouraging different levels of engagement.

Images play a significant role in all social media. For example, Instagram requires that every post contain an image,[1] while other platforms, such as Twitter, rely more on users posting primarily words (Forsey, 2020). Consistent with prior research on multimodal communication (Barberá-Tomás et al., 2019; Zamparini & Lurati, 2017), both are needed to elicit sentiment from social media users (Wang & Li, 2015), and social media users who post images and words see substantially more engagement with their posts (Cooper, 2019). However, we argue that images will have a greater relative influence than words on the number of followers, and words will have a greater relative influence than images on followers' positive interactions.

Given that image processing is rapid, unmediated, vivid, and can provide visual and heuristic "proof" that is easier to process (Kahneman et al., 1982), we argue that images are likely to have a greater influence on the less cognitively effortful decision to follow an influencer. However, because images are syntactically indeterminant, they cannot communicate more direct and specific information about the influencer's interest in particular individuals, although their syntactic indeterminacy can also make it easier to interpret images in ways that confirm their initial perceptions. Thus, while they can stimulate liking and perceived confidence (Messaris, 1997) that leads to following, they are less likely to stimulate higher-level engagement, such as responding positively to the influencers' posts, particularly since this action employs a different communication mode (i.e., responding to posts using words).

Although words are processed more slowly than images, their syntactic determinacy (Messaris, 1997) lets them create more precise linkages and causal associations (Meyer et al., 2018) that convey the specific information and arguments followers need to assess whether the influencer can help them meet their goals. Words can also evoke affective responses (Camerer, Loewenstein, & Prelec, 2005; Slovic, Finucane, Peters, & MacGregor, 2004) that enhance followers' attraction to, and trust in, the individual communicating (Finucane et al., 2003; Semin & Fiedler, 1988; Zajonc, 1980) by aligning their perceptions and public actions (Cialdini, 2004; Festinger, 1957). Tausczik and Pennebaker (2010: 32) noted, "the degree to which people express emotion, how they express emotion, and the valence of that emotion can tell us how people are experiencing the world."

Thus, while both modes are likely influential on the decisions to follow and positively interact with the influencer, we expect that words are more important than images in affecting followers' decisions to positively interact with influencers, because this higher-level engagement behavior requires more cognitive effort (Ashley & Tuten, 2015), and words can convey a specific message that may better, or more strongly, motivate liking and trust, or efforts to meet different goals (e.g., meet their fitness objectives, or be part of a social community) (Tuškej et al., 2013). We therefore hypothesize:

Hypothesis 1a. Image-based cues will have a stronger positive relationship with the influencer's number of followers compared to word-based cues.

Hypothesis 1b. Word-based cues will have a stronger positive relationship with followers' positive interaction with the influencer compared to image-based cues.

The Big-Two Information Cues: Warmth and Competence

Like the communication's mode, we expect the communication's content to affect engagement behaviors differently. Decades of research (e.g., Eagly, 1987; Rosenberg, Nelson, & Vivekananthan, 1968; for a review, see Abele & Wojciszke, 2014) has identified two fundamental dimensions individuals use to assess themselves and others: *warmth* and *competence* (Fiske et al., 2007).[2] Fiske and colleagues (2007: 77) noted, "the warmth dimension captures traits that are related to perceived intent, including friendliness, helpfulness, sincerity, trustworthiness and morality, whereas the competence dimension reflects traits that are related to perceived ability, including intelligence, skill, creativity and efficacy." Thus, for example, "warmth judgments affect how much we trust versus doubt others'

[1] While some images can contain words, they make up less than 5% of all images in our sample. Further, they frequently consist of quotes from famous individuals, or repeat what is written in the post itself. Thus, we did not include these in our analysis, but talk about how future research may address them in the Discussion section.

[2] We employ Fiske et al.'s (2007) labels because they most closely match the constructs we are interested in. However, psychologists have employed a variety of other labels to capture these constructs over the years, including agentic and communal, masculinity and femininity, intellectually versus socially good-bad, and instrumentality and expressiveness, to name a few (Abele & Wojciszke, 2014).

motives, whereas competence judgments affect assessments of others' ability to effectively enact their motives" (Cuddy, Glick, & Beninger, 2011: 74). Further, research in a variety of contexts using different methods has shown that warmth is judged temporally before, and is given greater weight than competence when judging others (Abele & Wojciszke, 2014; Fiske et al., 2007).

Although prior research has considered whether attentiveness to one dimension or the other is affected by individual characteristics (e.g., gender, membership in an individualist or collectivist culture), and situational factors (e.g., whether information is framed as being from the individual's or observer's perspective) (Cuddy et al., 2011), scholars have generally made comparisons between the relative effects of warmth and competence on a single outcome, rather than comparing their relative effects across different outcomes. Further, researchers have not explored how warmth and competence cues can vary in influencing behaviors that require different levels of cognitive effort and different motivations.

The relative effects of competence and warmth on following and positive interactions. As discussed earlier, individuals will expend limited cognitive effort in deciding whether to take low-level engagement behaviors (Ashley & Tuten, 2015). Further, when assessing entrepreneurs that provide experience goods—where product quality is unknown until the product is consumed (e.g., wine, air travel, massages—or, in our case, fitness advice and training)—individuals first look for clues that the entrepreneur has the capabilities to provide the service. While they will also look for evidence that the entrepreneur is likable and interesting, if they do not appear capable and competent then individuals are unlikely to follow them, or to continue following them. Thus, individuals seeking to assess an influencer's competence will look for evidence that they have the knowledge and abilities they claim (Chaiken, 1980; Cuddy et al., 2011), since individuals treat positive information (i.e., evidence that supports the claim) as more diagnostic when judging competence (Skowronski & Carlston, 1987). Further, unless followers have the experience necessary to validate their claims (Wagner & Sternberg, 1985), they may not even attempt to do so (Malhotra & Bazerman, 2008). Thus, if the influencer provides cues that suggest they are competent, individuals will be more likely to follow them, exerting little further effort on the decision.

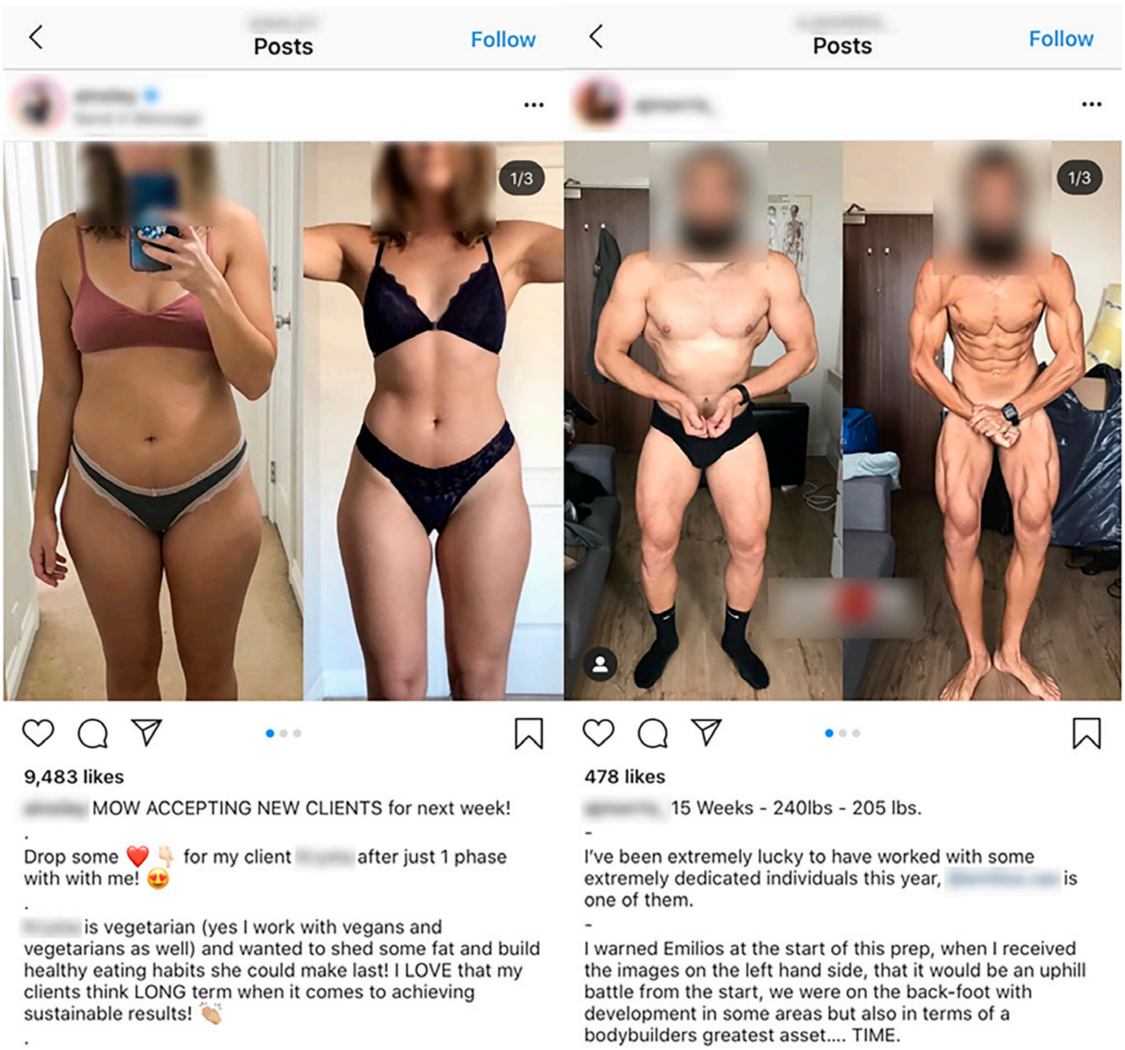
Fitness influencers can use both words and images to communicate their competence. For example, providing workout routines and describing how to properly execute the exercises can indicate their knowledge and expertise. Images can play a similar role, by visually showcasing the influencer's expertise and qualifications (Carrotte, Vella, & Lim, 2015; Pinto & Yagnik, 2017; Teodoro & Naaman, 2013). Fitness influencers post images of their physiques, or of themselves doing workouts, as well as "before and after" photos of themselves or their clients, as evidence of their capabilities. Figure 1 shows examples of clients' before and after images, and Figure 2 provides examples of fitness influencers' own images. These images indicate the influencer's competence, because receivers can treat them as an "informational characteristic that credibly indicates underlying quality" (Clough, Fang, Vissa, & Wu, 2019: 248).

However, when deciding whether to take higher-level engagement behaviors, such as positively interacting with the influencer, individuals need to experience higher levels of positive affect toward, and trust in, the influencer (Ashley & Tuten, 2015; Tuškej et al., 2013; van Doorn et al., 2010). Although followers may respect the influencer's competence, they may also be more likely to perceive them as capable, but cold and distant (Cuddy et al., 2011). This is in part why voters express preferences for politicians they would "like to have a beer with" over those who have more impressive resumes and credentials, but who they perceive as less approachable and more "elite" (Caprara & Zimbardo, 2004).

In contrast to competence cues, warmth cues increase the trustworthiness, likeability, and authenticity (Abele & Wojciszke, 2014; Fiske et al., 2007) necessary for higher-level engagement. Indeed, their ability to increase liking and trustworthiness is why prior research has typically found warmth cues to be more influential than competence cues (Cuddy et al., 2011; Fiske et al., 2007). Liking and trustworthiness are also antecedents to higher-level engagement (van Doorn et al., 2010);[3] thus, warmth cues can also motivate higher-level engagement behaviors because they can enhance their antecedents, increasing the likelihood the follower will want to pursue relational goals and expend greater cognitive effort (van Doorn et al., 2010).

[3] However, influencers' warmth cues are only likely to affect higher-level engagement when followers do not think the influencer has an ulterior motive (Jones, 1990) and perceive their communications as authentic. If followers perceive influencers as inauthentic, they will be less likely to respond positively to them (Fox & Stafford, 2020).

FIGURE 1
Example of Image-Based Competence Cues: Before and After Images



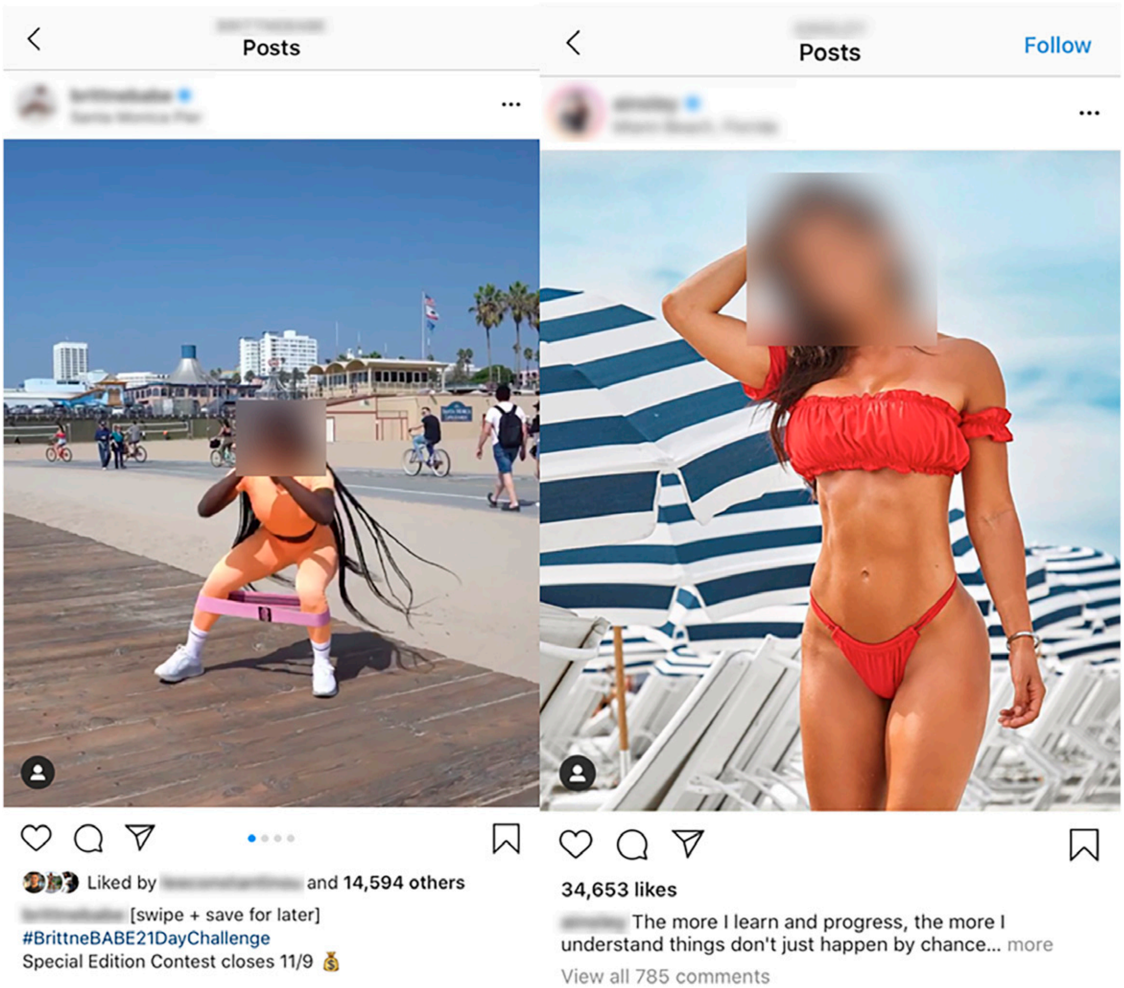
Like competence cues, we argue that words and images can convey warmth cues. A primary way in which influencers provide warmth cues is by using emotional language oriented toward others (as opposed to emotional language focused on themselves) in their posts. This illustrates the influencer's "relational orientation," or their desire to cultivate, foster, and maintain relationships with others (Gelfand et al., 2006), which is what warmth cues indicate[4] (Abele & Wojciszke, 2014; Fiske et al., 2007). To the extent that followers engage with the influencer by responding with positive emotional posts of their own, they may perceive they have a "relationship" with the influencer[5]—further promoting liking and trust (Chambers, 2013).

Influencers can also provide warmth cues through images. In addition to posting images of themselves

[4] Indeed, warmth cues' community focus is why Abele and Wojciszke (2014) preferred the term "communal" for this construct.

[5] We hasten to note, however, that these online relationships rarely reflect, or result in, personal "face-to-face" relationships and interactions. Rather, they reflect the "one-to-many" interactions that influencers have with hundreds, to hundreds of thousands, of followers (De Veirman, Cauberghe, & Hudders, 2017; Lou & Yuan, 2019). Nonetheless, followers often perceive them in more personal terms because the influencer has directed attention toward them, and others who observe these relationships may be motivated to follow the influencer as well.

FIGURE 2
Example of Image-Based Competence Cues: Self-Portrait or Demonstration Images



or their clients to prove their capabilities, influencers post images of a more personal nature, such as group photos with others, their vacations or other activities, children, pets, sunsets, and so on. These images are warmth cues because they demonstrate the influencer's community focus, create liking (Abele & Wojciszke, 2014), and can foster a sense of social similarity (e.g., "I love puppies, too!"). Figures 3 and 4 provide examples of the communal and personal images influencers post.

We argue that the need for warmth and competence cues can vary by level of engagement. Specifically, we expect competence cues to have a greater effect than warmth cues on the low-engagement behavior of following an influencer, and that warmth cues will have a greater effect than competence cues on the high-engagement behavior of positively interacting with the influencer. When deciding to follow a fitness influencer, individuals are likely looking for influencers who appear knowledgeable about fitness. In contrast, we expect warmth cues that promote liking and trust to play a greater role in deciding to positively engage with an individual, because it is a more cognitively effortful behavior, where liking and trust play more significant roles than they do in simply following an influencer (Cuddy et al., 2011), and whether the individual likes the influencer is more relevant in deciding to positively interact with them. We therefore hypothesize:

Hypothesis 2a. Competence cues will have a stronger positive relationship with an influencer's number of followers compared to warmth cues.

Hypothesis 2b. Warmth cues will have a stronger positive relationship with followers' positive interaction with the influencer compared to competence cues.

FIGURE 3
Example of Image-Based Warmth Cues: Communal or Social Images

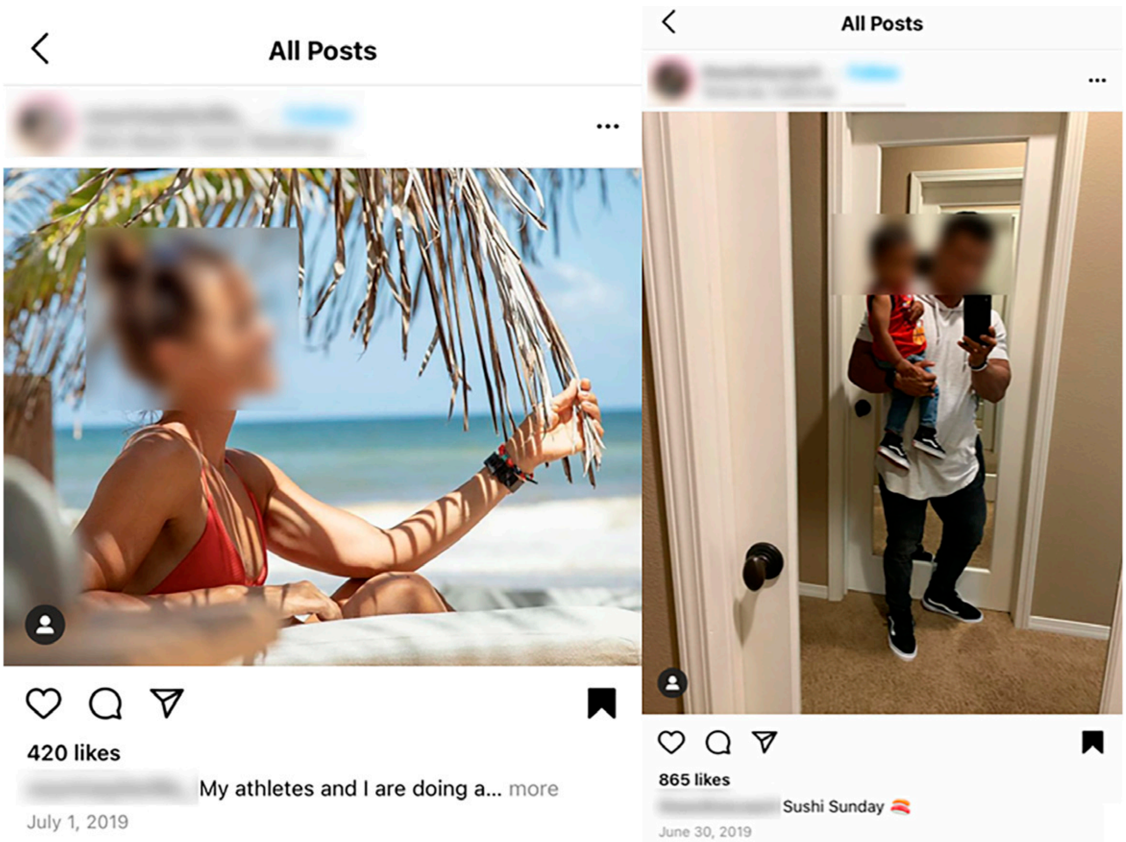
DATA AND RESEARCH METHOD

Sample: Fitness and Nutrition Industry Influencers

The fitness industry is large (revenues of $33.7 B in 2018; 12.1% from fitness training alone) and growing (Cohen, 2018). In the offline world, fitness trainers are typically required by brick-and-mortar gyms to have a specific level of accreditation, which allows them to demonstrate their capabilities based on where they received their certifications or degrees. While there are multiple certifying bodies (e.g., National Strength and Conditioning Association, Yoga Alliance, Precision Nutrition), the industry has no regulatory governing body. Thus, on social media, while some fitness trainers possess and tout their credentials, many fitness trainers forgo accredited certifications (Melton et al., 2008) and attract clients through other means. This presents an ideal context to assess the roles that images, words, and the competence and warmth cues they convey can play in encouraging individuals to follow and engage with the influencer.

To learn more about this phenomenon and better understand individuals' decisions to follow and engage with these entrepreneurs, in March of 2019 we attended the Arnold Fitness Expo, the largest annual fitness conference in the United States. We observed and interacted with consumers who had and had not yet made purchases from some of the influencers attending the expo. We saw that consumers had strong emotional responses to simply seeing some fitness influencers in person, ranging from screaming their names to almost hyperventilating. This further illustrated the role that emotions were playing in the consumers' responses. We then collected secondary data about Instagram fitness and nutrition industry influencers (i.e., those selling their own

FIGURE 4
Example of Image-Based Warmth Cues: Personal or Daily-Life Images



products or services principally over Instagram) to determine how they amass followers and encourage positive interactions on social media.

The internet and social media are also growing at a rapid pace. More than 58% of the global population uses the internet, with over 4.4 billion internet users worldwide as of April 2019; 79% also use social media platforms, with a global increase of 13% since 2017 (Chaffey, 2019). While there are numerous social media platforms, the one with the largest number of influencers (Barker, 2018), second highest number of users (Greenwood, 2016), and highest amount of engagement is Instagram (Leone, 2018). BrandWatch, the world's largest social media monitoring firm, reported that 35% of all internet users are on Instagram, and the platform has growth of over 1 million new users monthly (Smith, 2019). Instagram is driven by users posting images followed by brief captions limited to 2,200 characters (Chaffey, 2019).

We created our sample using key terms to search Instagram, and stratified random sampling. To fit our definition of an influencer, the individual had to offer fitness or nutrition training, coaching, or programs online.[6] Our initial searches involved the keywords *trainer, online trainer, online coach, fitness coach*, and *fitness coaching*. These searches pulled hashtags, usernames, and profiles that incorporated these terms. We also searched users' following and follower lists to find additional online fitness and nutrition influencers that were not identified using the initial search terms. We then looked at the service offerings listed in their profile or on their associated website. We only used profiles that were public, did not require a login, and were in English.

We continued searching until the same fitness influencers started coming up repeatedly. This generated

[6] While some of these influencers may also have physical studios and train individuals in person (only 18.6% of the influencers in our sample even noted a physical location), to be included in our sample they had to train or provide their services online. We did not include individuals that just used their social media profiles for advertising or posting information about their brick-and mortar-businesses.

an initial sample of 1,002 fitness influencers. We then drew a stratified random sample based on the size of the influencer's Instagram following prior to the beginning of our study period to ensure variance across our sample. While we created the stratified sample based on one of our dependent variables, we took steps to ensure this did not bias our results, and that the influencers had sufficient followership variance (Botev & Ridder, 2014). We randomly drew influencers from the middle stratum in direct proportion to their representation in our overall sample. As the initial sample yielded more influencers in the middle stratum than the high and low strata, we oversampled from the lowest and highest strata, randomly drawing 10% of our sample from each stratum, resulting in a sample of 502 influencers. The individuals in our sample were mostly established influencers (average profile age of 5.2 years, $SD = 2.2$ years, ranging from 1 month to 9.1 years).

We tracked the influencers' activity from July 1 to December 31 of 2019 using an application programming interface (API) that allowed us to automate the data scraping process. We collected information on the influencers' profiles, posts, and comments on their posts. We began by pulling the influencers' data two days each week (Monday and Thursday, as these are the most popular days for engaging with followers) (Kopanakis, 2018). However, we soon realized that some of the influencers only posted, or discussed certain topics, on particular weekdays; we thus decided to increase our data collection to six days a week, excluding Sunday as this was the slowest day for both posts and engagement (Moreau, 2020). We went back and collected data for the missing days up to that point, and collected data six days a week moving forward. We ultimately collected a total of 52,148 influencer posts; 8,730,714 follower comments; and 620,505 influencer replies to follower comments. While we pulled daily data for influencers' posts and comments, since the number of followers does not dramatically change on a day-to-day basis (Child, Haridakis, & Petronio, 2012), monthly observations allowed us to better understand between-influencer differences. We therefore aggregated these posts, comments, and replies to 3,012 influencer-month observations. To account for influencers who left the industry during our sampling period, we removed all influencers who did not post for the last three months of our time frame (i.e., no posts from October to December). This reduced our final pooled cross-sectional sample to 488 influencers and 2,928 influencer-month observations.

Dependent Variables[7]

Number of followers. We operationalized an influencer's ability to attract followers as the number of followers the influencer had at the end of each month, collected from the influencer's profile. As discussed earlier, the number of followers an influencer has enables them to gain brand endorsements (Jin et al., 2019), increase their prioritization by the social media platform's algorithm (Milan, 2015), and expand their product line of goods and services (Tang et al., 2012). Although influencers gain and lose followers each month, the within-month change in followers is typically small (approximately 1.5% on average in our sample).[8] Since we focus on between-influencer differences, we therefore used the number of followers at the end of each month. Given this measures' wide range and right-skewness (from 40 to 12,895,427 followers in our sample—mean of 407,587; median of 50,597; standard deviation of 1,230,326; and positive skew of 7.19) we log-transformed the measure (Hansen, 2019), reducing the skew to −0.21, which puts it within the normal range of −1.96 to 1.96.[9]

Positive interactions. We calculated positive interactions using the positive affect dictionary in Linguistic Inquiry Word Count (LIWC) (Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007).[10] We content-analyzed followers' responses to the influencer's posts, counting the number of positive affect words used by others in the comments portion of the influencer's posts.

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[7] All measure operationalizations, and where in the influencers' profiles they were obtained, are summarized in Table S-1 of the online supplement, which can be found at https://doi.org/10.6084/m9.figshare.22087460.v1.

[8] Average monthly percentage changes in followers are summarized in Table S-2 of the online supplement.

[9] During one data collection period in August our API underwent a substantial upgrade without warning; we lost data for the dependent variable for 119 influencers during that period. When assessing whether the missing data affected our findings, we compared models with missing data and the mean of all observations where we had the missing data; the variables had a 1.00 correlation and changes in results were minimal, indicating that the models are essentially identical. We therefore employed the data using the mean for the missing data in our analyses.

[10] We used positive interactions as our dependent variable instead of the raw number of comments to illustrate stakeholder actions requiring a higher-level of cognitive effort (e.g., comments using numerous positive affect words require more effort than a one-word comment).

Independent Variables[11]

Word-based cues. We created two word-based cues: (a) *word-based competence cues* and (b) *word-based warmth cues*. We collected the variables for each measure from the influencer's individual posts on their own Instagram profile, not their followers' profiles. Following prior social media research that has leveraged LIWC dictionaries to account for an individual's expertise (Fox & Stafford, 2020), we operationalized word-based competence cues using a three-variable index consisting of: (a) the number of analytic words used in the influencer's posts, (b) the number of analytic words used in the influencer's replies to comments, and (c) the number of first-person singular pronouns (i.e., "I," "me," "my") used in the influencer's posts. We measured these variables using the analytic and pronoun dictionaries in LIWC (Pennebaker et al., 2014). The analytic dictionary measures words that suggest "analytic or formal … thinking" (Boyd & Pennebaker, 2015: 573), which are frequently associated with more formal education (Pennebaker et al., 2014) and more complex reasoning (Jordan et al., 2019). Analytic language is considered less friendly and more rigid and cold (Pennebaker et al., 2014). Some examples of high analytic word count posts are: "Cable Tricep Kickbacks … Upper arm should be parallel to the ground and stay there! Control the weight in both directions! Add a pause at the top to intensify the contraction!!" or

> I find working with moderate weight for reps and dynamic drop sets are the way to go to consistently, safely breakdown muscle in a pressing motion. Make sure to deeply stretch each rep, creating as much engaged range of motion as possible. Fully extended and squeeze chest at maximum contraction.

To capture whether influencers talked about their own competence, we counted the number of first-person singular (e.g., I, my) pronouns (Lentz, 2017). An example of a post with a high number of self-oriented pronouns is "I see. I want. I grind. I get."

We operationalized the influencers' word-based warmth cues using a three-variable index comprised of: (a) the number of positive affect words used in the influencer's posts, (b) the number of positive affect words used in the influencer's replies to comments (Pollock & Rindova, 2003; Tetlock, Saar-Tsechansky, & Macskassy, 2008), and (c) the volume of other-inclusive, first-person plural (e.g., we, us) and second person (e.g., you, your) pronouns (Lentz, 2017) used in the influencer's posts, measured using the positive affect and pronoun dictionaries in LIWC (Pennebaker et al., 2007). We focused on positive affect because the Cronbach's α between positive and total affect was 0.97, indicating that almost all affective language was positive. These measures capture both the positivity of the influencers' posts and replies, and the extent to which they are focused on others as opposed to just themselves. Examples of posts with high positive affect are: "When preparation & opportunity meet … #alwaysbelieveinyourself #onelifetolive #noregrets #passionrules #love #create #inspire" or "Happy New Years Eve. I know everyone's super eager for this new decade! I know I am! It's very exciting and I love all the positive energy people are ready to share with the world! #2020." Examples of replies with high positive affect are: "Thanks for the love friend!" "I can't agree more!" and "oh yay! Congratulations! We're on the home stretch." Examples of posts with a high number of relational pronouns relative to total words are: "You're stronger than you think. You got this," and "Just so you know-YOU ARE LIMITLESS! Happy Monday!"

Given that each of these word-based measures and their corresponding variables had different means and standard deviations,[12] we transformed them into *z*-scores and created a composite index for the influencer's word-based cues by taking the mean of the six *z*-scores (three variables for each word-based cue measure).[13]

[11] While competence and warmth have been thoroughly tested and validated, to validate our competence and warmth measures we recruited a sample of 93 Instagram users on Prolific (Zunino et al., 2021) and asked them to rate eight messages—four high in analytic language and four high in positive emotional language—on a 1–5 scale for each construct. *T*-tests comparing the mean rankings of each message confirmed that social media users perceived each measure as we intended. The messages and *t*-tests are presented Table S-3 of the online supplement.

[12] For word-based competence cues, the analytic posts, analytic replies, and self-oriented pronouns had means of 1,522.49, 77.28, and 44.39, and standard deviations of 1,614.47, 84.50, and 84.11, respectively. For word-based warmth cues, the number of positive affect words in posts, positive affect in replies, and the number of other-inclusive personal pronouns used had means of 80.65, 81.82, and 149.35, and standard deviations of 80.59, 102.94, and 310.40, respectively.

[13] We conducted *post hoc* analyses to determine the difference between summing and taking the average. The results were the same, so we chose the average. We also ran analyses using the individual measures, and none of them were significant by themselves.

Image-based cues. Similar to our word-based cue measures, we created two measures capturing (a) *image-based competence cues* and (b) *image-based warmth cues*. We used two different types of images to operationalize competence cues: (a) The number of posts showcasing client or personal transformations—that is, *before and after photos* of themselves or others—which captured how frequently the influencer provided "evidence" of their ability to bring others, or themselves, success; and (b) The number of posts showcasing their own "capabilities" using images of their bodies or abilities (i.e., workout demonstration pictures and videos), which we labeled *self-portraits*. The self-portraits had to showcase the individual's physique or knowledge of how to perform exercises. We excluded pictures in which the influencer was in a group (i.e., more than two people), as we coded these images separately as warmth cues. We also excluded images where the influencers' clothing (e.g., sweatsuit, dress, suit) obscured their physique, or their pose obscured a clear view of them (e.g., crouching, standing behind something or someone).[14] We combined the counts for each type of image into a single index, weighting each type of image equally, as we had no *a priori* basis for expecting whether their influence would differ. We calculated interrater reliability metrics on both types of images using three raters, who each independently evaluated 500 posts. Raters evaluated the still image for videos, as videos typically do not play on their own and the video stills are what viewers see when scrolling through a user's public page (West, 2017). Cronbach's α values were 0.91 for before and after images, and 0.73 for self-portrait images.

We also coded two different images as warmth cues: (a) *group images*, and (b) *personal life* images. Group images reflect the influencers' other-focused, communal orientation (Fisher, 2019) and included images with three or more individuals. Personal life images humanize the influencer, showing aspects of their lives that followers can relate to (e.g., kids, pets), or live vicariously through (e.g., vacations, beautiful sunsets or vistas, etc.) (Croes & Bartels, 2021). We combined the monthly counts for each image type into a single index measure. We excluded images that did not fall into either the warmth or competence categories (e.g., exercise equipment, screenshots of exercise lists).[15]

Given that the image-based cue measures also had different means and standard deviations,[16] we transformed them into *z*-scores and created a composite index for the influencer's image-based cues by taking the mean of the four *z*-scores (two variables for each image-based cue measure).

Competence cues. We used the same approach to create our composite *competence cue* measure, again taking the mean of the *z*-scores for the three word-based and two image-based competence cue measures.

Warmth cues. We used the same approach to create our composite *warmth cues* measure, again taking the mean of the *z*-scores for the three word-based and two image-based warmth cue measures.

Control variables. Because our predictor variables are calculated based on the number of words used by the influencer, to control for the frequency and length of communications we controlled for the number of words in influencers' posts and replies, and in followers' comments (i.e., *post, reply,* and *comment word counts*). We also controlled for the number of influencer-posted *posts in a period*, *comments*, and *replies to comments*, as influencers who are more active on social media are more likely to have greater positive interactions and higher follower counts (Dessart, 2017).

Given our focus on influencers' competence cues, and the fact that credentials such as degrees or certifications can influence stakeholder evaluations (Spence, 1973), we accounted for entrepreneurs showcasing their traditional *credentials,* which we collected from the biography section of the influencer's profile. We created a binary measure coded 1

[14] After we had collected the original 52,148 posts, some influencers deleted their posts. We performed additional analyses of the influence these missing variables had on our results and found that the model fit statistics were the same for both models with missing data and those that were coded as 0 when missing. Therefore, we use the model with the missing variables as we cannot code whether the post contained an image-based credential.

[15] This measure was not part of our initial analyses, and some posts had been deleted before we created this measure. Thus, it is based only on our undeleted posts.

[16] For image-based competence cues, the before and after images and self-portrait images had means of 0.81 and 7.84, and standard deviations of 1.79 and 8.78, respectively. For image-based warmth cues, the number of social images and personal images had means of 4.02 and 0.39, and standard deviations of 4.73 and 0.88, respectively.

if the influencer listed any certifications or degrees and 0 otherwise.[17]

We also controlled for influencers' *attractiveness* and *fitness* levels, since these could affect their number of followers and how followers communicated with them. This is because both can lead to increases in positive interactions and the number of followers (Yuan & Lou, 2020). Each measure was a dummy variable coded 1 if a rater panel assessed the influencers as attractive and fit, respectively, and 0 otherwise.

We used eight raters—four male, four female—ranging in age from 21 to 54, representing multiple ethnicities and nationalities. We instructed each rater to go through designated images for each of the influencers and rate their attractiveness and fitness. They were asked to evaluate attractiveness based on the Hatfield and Sprecher (1986: 4) definition of attractiveness: "that which represents one's conception of the ideal in appearance; that which gives the greatest degree of pleasure to the senses." We did not, however, provide a fitness definition, as we wanted to determine the raters' perceptions of fitness. We informed the raters that fitness may have been different from what they found attractive, and thus that they should not feel obligated to rate the same individual as both attractive and fit. Cronbach's α values were 0.61 for attractiveness and 0.79 for fitness; the lower α for attractiveness is not necessarily a problem, however, as it is consistent with previous research illustrating the subjective nature of individuals' perceptions of attractiveness (Cohn & Adler, 1992; Lovejoy, 2001), and we specifically structured our rater panel to capture diverse conceptions of attractiveness. That said, we assigned discrepant assessment ratings based on majority opinion; ties were resolved by two raters.

We also controlled for the *age of the influencer's profile*, calculated as the difference between the last day of the observation month and their first post ever made. Influencers who have been on Instagram longer have had more opportunity to grow their following, are likely to have a more stable number of followers, and are more likely to be beyond their early, high-growth phase. We controlled for the number of *video posts* in each period, as most posts were pictures (less than 19% of posts were videos), and the number of *deleted posts* each period, since some posts were deleted during the period when they were originally posted but before we collected them, and users could perceive this negatively (Yeager, 2020). We could see that the influencer had deleted a post as the content had been removed, but not its link.

Finally, we controlled for the entrepreneur's *gender* (male = 0 and female = 1) and *race (White or non-White,* with White coded 0 and non-White coded 1) based on their profiles and images, given that females and people of color comprise the majority of Instagram users (Tran, 2020). We used a binary rating because some individuals were multiracial, or their specific race was hard to discern. The entrepreneur's race was assessed independently by two individuals of varying ethnicities. The Cronbach's α of their ratings was 0.81.

Analysis Method

Certo, Withers, and Semadeni (2017) argued that it is important for researchers to theoretically establish whether they are interested in within- or between-actor variation, and to use the appropriate modeling technique. Because we are theorizing about between-influencer differences, we employed Hausman–Taylor (HT) random effects regression (Stata 16) using the *xthtaylor* command to analyze our data. We use a random effects model because our dependent variable is continuous, we have pooled cross-sectional data with multiple observations for the same individuals, we have important time-invariant and nearly time-invariant measures, and we are theorizing about between-actor effects rather than within-actor effects over time.

While random effects models allow for time-invariant variables that fixed effects regression does not (Greene, 2012), the possibility exists that some unobservable effects are uncorrelated with the explanatory variables, biasing the random effects estimators (Hansen, 2019). HT random effects regression allows us to account for random effects with panel data, while also accounting for time-invariant variables and covariates that are significantly correlated with the unobserved fixed effect (Hausman &

[17] Most of our sample (76%) possessed neither a certification nor a degree; however, we nonetheless conducted a more granular analysis of these cues. We compared (a) those who had a certification (0) with those that possessed a degree (1), (b) those with no credential (0) to those with a degree (1), and (c) those with no credential (0) to those with a certification (1). The only difference was between influencers with a certification and influencers with no credentials, who had more followers (β = 0.080, p = 0.048), but significantly lower positive interactions (β = −71.26, p = 0.028). This suggests that there may be differences in traditional credentials, and that more costly competence cues (e.g., a degree) may be less influential.

Taylor, 1981).[18] The HT estimator's consistency is based on the assumption that an unobserved fixed effect is correlated with our dependent variables, requiring instruments for the independent variables (both time-variant and time-invariant) that may also be significantly correlated with this fixed effect (Hansen, 2019).

For our study, the Instagram algorithm may be an unobserved, or fixed, effect since it plays a role in how often, and which influencer's, posts show up in a user's feed (Barnhart, 2021), but the factors included in the algorithm, and how they are weighted, is a closely guarded secret. This means that there could be variables that Instagram deems important in their algorithm that we are not controlling for. HT lets the user assign variables to time-variant and time-invariant exogenous and endogenous categories, and automatically calculates valid instruments for the endogenous variables (Hausman & Taylor, 1981).[19] Exogenous variables are uncorrelated with our fixed effect (Instagram's algorithm); they include the influencer's gender, ethnicity, credentials, perceived attractiveness and perceived fitness. The endogenous variables include variables such as how often an influencer posts each period, how long their profile has been active, and the amount of comments and replies to comments, respectively. These all play a role in how often influencers' posts appear on users' feeds (Barnhart, 2021).

Finally, because testing our hypotheses required that we compare coefficients, and the predictors were scaled differently, we standardized the coefficients for our key independent variables so that we could conduct Wald tests using the *test* command in Stata.

RESULTS

Entrepreneurs in our sample were active on Instagram for about five years and averaged about 18 posts a month. Our sample is predominantly female (63%) and non-White (79%), which is similar to Instagram's current gender and ethnicity distribution (Tran, 2020). Table 1 presents the descriptive statistics and correlation matrix.

Table 2 presents the models testing our hypotheses.[20] Models 1 and 4 include the control variables only, Models 2 and 5 add the aggregated image- and word-based cues to test Hypotheses 1a and 1b, and Models 3 and 6 include the aggregated competence and warmth cues to test Hypotheses 2a and 2b.[21] Table 3 summarizes the Wald tests (Davidson & MacKinnon, 1993) for each comparison. The columns on the left summarize the standardized coefficients from Table 2; the columns on the right present the Wald tests for Hypotheses 1a and 1b and 2a and 2b.

Hypothesis 1a predicted that image-based cues would have a stronger positive relationship with the influencer's number of followers compared to word-based cues. As shown in Table 2 and Table 3, while image-based cues have a positive, significant relationship with number of followers ($\beta = 0.02$, $p = 0.04$), word-based cues do not ($\beta = -0.02$, $p = 0.54$). Although the image-based cues coefficient is more positive than the word-based cues coefficient, the Wald test in Table 3 shows that these coefficients are not significantly different ($\chi^2 = 1.29$; $p = 0.26$), likely due to the large confidence interval (–0.08 to 0.04) for word-based cues.[22] Thus, although the statistical significance pattern is consistent with our hypothesis, since Hypothesis 1a focuses on relative effect sizes it is not supported. We used the *margins* and *lincom* commands in Stata to determine the effect size for the significant image-based cue relationship, holding all binary variables (i.e., gender, attractiveness, fitness, ethnicity) at their mode and all continuous variables at their mean. For every 1 standard deviation increase in image-based cues, influencers gain an additional 1,498 followers, an increase of 1.74%.

Hypothesis 1b predicted that word-based cues would have a stronger positive relationship with followers' positive interactions with the influencer compared to image-based cues. As shown in Model 5 of Table 2, word-based cues ($\beta = 545.49$, $p = 0.00$)

[18] Findings from random effects regression (*xtreg* in Stata) show consistent findings with Hausman and Taylor (1981).

[19] HT stipulates that there needs to be "at least as many exogenous time-varying regressors as endogenous time-invariant regressors" and robust standard errors must be clustered to account for heteroskedasticity (Hansen, 2019: 647).

[20] We include full HT regression results using unstandardized independent variables in Table S-4 of the online supplement.

[21] We also tested for curvilinear effects of both image- and word-based competence and warmth cues, but none of these tests were significant.

[22] The confidence intervals take on negative values because the measures are standardized *z*-scores, which also take on negative values for observations with values below the mean.

TABLE 1
Descriptive Statistics and Correlations

	Mean	*SD*	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Number of followers	407,586.5	1,230,326	40.00	12,895,427.00	1																			
2. Positive emotional interactions	1,317.10	2,754.69	0.00	30,110.00	0.66*	1																		
3. Post word count	2,186.38	2,285.52	0.00	19,171.00	0.08*	0.24*	1																	
4. Reply word count	1,340.82	2,468.37	0.00	31,842.00	0.12*	0.40*	0.40*	1																
5. Comment word count	15,883.05	37,351.16	0.00	553,584.00	0.57*	0.94	0.23*	0.33*	1															
6. Posts in period	17.78	14.34	1.00	116.00	0.25*	0.36*	0.65*	0.29*	0.32*	1														
7. Number of comments	2,981.30	9,442.40	0.00	234,659.00	0.57*	0.83*	0.09*	0.18*	0.89*	0.23*	1													
8. Number of replies to comments	211.82	444.75	0.00	6,057.00	0.16*	0.39*	0.31*	0.92*	0.31*	0.27*	0.20*	1												
9. Video posts	3.29	5.14	0.00	45.00	0.19*	0.23*	0.29*	0.14*	0.22*	0.61*	0.16*	0.14*	1											
10. Deleted posts	0.28	1.33	0.00	33.00	−0.00	−0.03	0.00	−0.03	−0.03	0.16*	−0.02	−0.01	0.06*	1										
11. Attractiveness	0.65	0.48	0.00	1.00	0.14*	0.16*	0.01	0.09*	0.11*	−0.03	0.11*	0.10*	−0.05*	−0.11*	1									
12. Fitness rating	0.83	0.38	0.00	1.00	0.11*	0.10*	−0.00	0.08*	0.08*	0.09*	0.07*	0.09*	0.12*	−0.06*	0.20*	1								
13. Age of profile	5.21	2.17	0.04	9.07	0.15*	0.14*	0.04*	0.10*	0.13*	0.10*	0.10*	0.08*	0.05*	−0.09*	0.13*	0.20*	1							
14. Gender	0.63	0.48	0.00	1.00	0.09*	0.16*	0.05*	0.12*	0.10*	−0.03	0.08*	0.11*	−0.14*	−0.03	0.18*	−0.10*	0.10*	1						
15. Ethnicity	0.21	0.41	0.00	1.00	0.03	−0.03	−0.12*	−0.02	−0.04*	0.03	0.00	−0.01	0.10*	0.02	0.04*	0.01	−0.04*	−0.19*	1					
16. Credentials	0.18	0.38	0.00	1.00	−0.07*	−0.04*	0.03	0.01	−0.03	−0.06*	−0.06*	−0.02	−0.04*	0.02	−0.02	−0.05*	0.07*	0.06*	−0.09*	1				
17. Image-based cues	0.00	0.63	−0.66	4.48	0.24*	0.34	0.47	0.24	0.30	0.78	0.22	0.21	0.53	−0.08	0.07	0.14	0.17	0.04	0.02	−0.09	1			
18. Word-based cues	0.00	0.81	−0.78	5.70	0.11*	0.36	0.90	0.72	0.32	0.61	0.15	0.61	0.27	−0.01	0.08	0.04	0.08	0.15	−0.11	0.02	0.48	1		
19. Competence cues	0.00	0.71	−0.75	4.71	0.18*	0.39	0.84	0.61	0.35	0.74	0.19	0.51	0.42	−0.04	0.06	0.10	0.12	0.09	−0.06	0.01	0.69	0.90	1	
20. Warmth Cues	0.00	0.66	−0.72	3.74	0.15*	0.28	0.80	0.59	0.33	0.69	0.19	0.52	0.35	−0.04	0.11	0.06	0.13	0.15	−0.09	−0.05	0.73	0.88	0.79	1

Note: $n = 2{,}928$.
* $p < .05$

TABLE 2
Hausman–Taylor Regression Results (Standardized IVs)

	DV: LN Number of Followers			DV: Positive Interactions		
	(1)	(2)	(3)	(4)	(5)	(6)
Time-Invariant Exogenous						
Attractiveness rating	1.22***	1.21***	1.21***	228.72***	193.03**	216.15***
	(0.24)	(0.24)	(0.24)	(61.39)	(61.21)	(58.32)
Fitness rating	1.07***	1.06***	1.05***	44.63	-14.93	50.69
	(0.29)	(0.29)	(0.29)	(110.42)	(97.49)	(95.40)
Gender	0.56*	0.55*	0.54*	412.03***	332.05***	391.18***
	(0.23)	(0.23)	(0.23)	(86.06)	(77.84)	(79.53)
Ethnicity	0.13	0.13	0.13	119.87	134.39	122.63
	(0.26)	(0.26)	(0.26)	(123.79)	(123.86)	(124.06)
Time Variant Endogenous						
Age of profile	0.19***	0.20***	0.21***	75.44	113.02†	62.08
	(0.04)	(0.04)	(0.04)	(75.75)	(64.31)	(62.96)
Posts in period	−0.00	−0.00	−0.00	11.08***	9.60**	5.99†
	(0.00)	(0.00)	(0.00)	(3.11)	(3.27)	(3.40)
No. of comments	−0.00	−0.00	−0.00	−0.04***	−0.04***	−0.04***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
No. of replies	−0.00	−0.00	−0.00	0.76**	0.75**	0.74**
	(0.00)	(0.00)	(0.00)	(0.24)	(0.23)	(0.23)
Post word count	−0.00	0.00	−0.00	−0.01	−0.20***	−0.06**
	(0.00)	(0.00)	(0.00)	(0.02)	(0.04)	(0.02)
Comment word count	0.00	0.00	0.00	0.06***	0.06***	0.06***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Reply word count	0.00†	0.00	−0.00	0.00	−0.09	−0.02
	(0.00)	(0.00)	(0.00)	(0.04)	(0.05)	(0.05)
Time-Variant Exogenous						
Video posts	0.00	0.00	0.00	−3.60	−4.74	−2.20
	(0.00)	(0.00)	(0.00)	(4.45)	(4.36)	(4.31)
Deleted posts	0.00	0.01	0.01	−18.36†	−13.55	−9.03
	(0.01)	(0.01)	(0.01)	(9.45)	(9.24)	(9.03)
Traditional credentials	0.04	0.04	0.04	−80.73*	−68.36†	−70.61†
	(0.03)	(0.03)	(0.03)	(39.22)	(40.24)	(38.82)
Image-based cues		0.02*			50.99†	
		(0.01)			(28.08)	
Word-based cues		−0.02			545.49***	
		(0.03)			(137.81)	
Competence cues			0.05*			77.97
			(0.02)			(73.99)
Warmth cues			0.00			141.43***
			(0.01)			(34.83)
Constant	7.54***	7.50***	7.53***	−741.75*	−250.71	−422.23***
	(0.35)	(0.35)	(0.35)	(319.30)	(320.07)	(306.23)
n	2,916	2,916	2,916	2,916	2,916	2,916
VIF[27]	4.72	6.47	4.99	4.72	6.47	4.99
Collinearity diagnostics	12.90	20.00	15.86	14.40	16.87	14.88
χ^2	10,559.78***	10,702.95***	10,707.51***	2,356.11***	2,707.08***	2,756.42***
Degrees of freedom	14	16	16	14	16	16

Note: Standard errors in parentheses. While VIFs below 10 are considered acceptable (Hair, Anderson, Tatham, & Black 1995), removing the number of influencer replies lowered model VIF statistics to 4.90 for both followers and positive interactions, below the ideal value of 5 (Hair, Ringle, & Sarstedt, 2011), without changing our results.

† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

TABLE 3
Hypothesis Testing and Wald Test Results

Dependent Variable	Variable	β^*	Sig. Value	Variables Compared	Wald Test χ^2	Wald Sig. Value	Hypothesis and Result
LN Number of Followers	Images	0.02	0.04*	Images to Words	1.29	0.26	1a
	Words	−0.02	0.54				*Not Supported*
	Competence	0.05	0.02*	Competence to Warmth	6.26	0.01*	2a
	Warmth	0.00	0.64				*Supported*
Positive Interactions	Images	50.99	0.07†	Images to Words	11.89	0.00**	1b
	Words	545.49	0.00***				*Supported*
	Competence	78.00	0.29	Competence to Warmth	0.66	0.42	2b
	Warmth	141.43	0.00***				*Not Supported*

* All β values in the table are standardized to compare coefficients for hypothesis testing.

have a positive and significant relationship with positive interactions, and image-based cues have a positive, marginally significant (β =50.99, p = 0.07) relationship with positive interactions. The Wald test in Table 3 shows that the coefficient for word-based cues is significantly larger (χ^2 = 11.89; p = 0.00); Hypothesis 1b is thus supported. We again used the *margins* and *lincom* commands in Stata to estimate the effect sizes for both image- and word-based cues, and found that for every 1 standard deviation increase in word-based cues and image-based cues, influencers increase their positive interactions by 36.8% and 3.4%, respectively.

Hypothesis 2a predicted that competence cues would have a stronger positive relationship with an influencer's number of followers compared to warmth cues. As shown in Table 2, competence cues have a positive, significant relationship with the influencer's number of followers (β = 0.05, p = 0.02), but warmth cues do not (β = 0.00, p = 0.64). Further, the Wald test in Table 3 shows the competence cue coefficient is significantly larger (χ^2 = 6.26; p = 0.01). Thus, Hypothesis 2a is supported. We again used the *margins* and *lincom* commands in Stata to estimate the effect sizes for competence cues, and found that for every 1 standard deviation increase in competence cues, influencers gain an additional 4,353 followers, an increase of 5.1%.

Hypothesis 2b predicted that warmth cues would have a stronger positive relationship with followers' positive interactions with the influencer compared to competence cues. As shown in Table 2, warmth cues have a positive, significant relationship with the influencer's positive interactions (β = 141.43, p = 0.00), but competence cues do not (β = 78.00, p = 0.29). However, while the warmth cue coefficient is larger than the competence cue coefficient, the Wald test in Table 3 shows that there is no significant difference between the two variables (χ^2 = 0.66; p = 0.42), again likely due to the large confidence interval for competence cues (−67.05 to 222.99). Thus, although the statistical significance pattern is consistent with Hypothesis 2b, since the hypothesis focuses on relative effect sizes it is not supported.

Robustness Tests

Within-mode and cue content comparisons. In testing our hypotheses we collapsed across cue content (competence and warmth) to test mode effects, and across mode (images and words) to test cue content effects. However, it is possible that we might observe different effects if we control for content when comparing mode (e.g., comparing image- versus word-based competence cues) and cue content (e.g., comparing image-based competence vs. image-based warmth cues). We reran our analyses (see Table S-5 and Table S-6 in the online supplement) and found that image-based competence cues have a positive and significant relationship with number of followers (β = 0.03, p = 0.01), while word-based competence cues do not (β = 0.02, p = 0.38). However, the Wald test shows that these coefficients are not significantly different (χ^2 = 0.13; p = 0.72). In contrast, image-based warmth cues are not significantly related to number of followers (β = 0.01, p = 0.17), but word-based warmth cues are negatively and significantly related (β = −0.04, p = 0.03). The Wald test shows that these coefficients are significantly different (χ^2 = 4.75; p = 0.03). Although word-based warmth cues have the opposite effect to that anticipated, the difference is still in the direction we expected.

Image-based (β =−0.94, p = 0.98) competence cues do not have a significant relationship with positive interactions, but word-based competence cues do (β = 244.67, p = 0.02). Further, the Wald test shows that these coefficients are significantly different from each other (χ^2 = 4.47; p = 0.04). Both image-based (β = 41.00, p = 0.03) and word-based (β = 307.312, p = 0.00) warmth cues have positive, significant relationships with positive interactions, and the Wald test shows that the word-based cue coefficient is significantly larger (χ^2 = 8.75; p = 0.00).

When comparing within modes but across cues, we see additional differences (the coefficients are the same as reported above). Image-based competence cues have a larger effect on the influencer's number of followers than image-based warmth cues (χ^2 = 4.43; p = 0.04). However, when looking at the effects of word-based cues on number of followers we see that warmth cues' negative relationship is larger than competence cues' nonsignificant but positive relationship (χ^2 = 5.02; p = 0.03). With respect to positive interactions, we find that even though image-based warmth cues have a positive, significant relationship with positive interactions and image-based competence cues do not, the coefficients are not significantly different (χ^2 = 1.23; p = 0.27). When considering word-based cues, we again find that the significant effects of competence and warmth cues with positive interactions are not significantly different (χ^2 = 0.22; p = 0.64). The nonsignificant Wald tests, despite the differences in coefficients, are likely due to the large confidence intervals for the competence cue measures.

Since we expected images and competence cues to have the biggest effects on followers, and words and warmth cues to have the biggest effects on positive interactions, we also compared image-based competence cues and word-based warmth cues. As expected, image-based competence cues had a larger effect on followers (χ^2 = 10.69; p = 0.00) and word-based warmth cues had a larger effect on positive interactions (χ^2 = 8.00; p = 0.01).[23] These results are interesting, because while generally consistent with our primary analyses, they also illustrate that different mode–cue content combinations may be more or less effective in stimulating different levels of engagement.

Outliers and influential variables.[24] Given the extremes in number of followers reflected in our dependent variables' large skew, we also sought to understand whether our results were influenced by extreme outliers. We winsorized our skewed variables (dependent variables ln number of followers and positive interactions; and the control variables *comments in period, replies in period, post word count, reply word count, comment word count, posts deleted, and video posts)* using the *winsor* command in Stata with a 1% cutoff, and reran our analyses to determine whether the skew was influencing results (see Tables S-7 and S-8 in the online supplement). However, the only changes were image-based cues losing their marginal significance with followers, and competence cues being slightly less significant (but still significant at $p < .05$). We also ran an additional regression excluding our control variables to understand the collinearity effects,[25] and the effects of our predictor variables remained consistent. Finally, we ran tests including both lagged dependent variables, and, separately, using lagged independent variables. The only changes in both instances were that the marginally significant relationship between image-based cues to positive interactions was no longer significant.

Emoticons. Another potential issue unique to social media is that many of the posts and comments included emoticons—that is, graphical images used to express reactions or emotions. As LIWC does not interpret images, we leveraged the emoticon dictionaries from Apple and Android, the two most common mobile phone platforms used to post on social media, to account for the sentiment expressed in emoticons, as these were frequently used in posts and previous research has shown that they play a role in sentiment analysis (Barbieri, Ballesteros, & Saggion, 2017; Novak, Smailović, Sluban, & Mozetič, 2015). We used these dictionaries to substitute text for the emoticon images, which we could then analyze using

[23] Word-based competence cues and image-based warmth cues did not have significantly different effects on either engagement behavior.

[24] Given that many social media variables were correlated with our dependent variables, as illustrated in Table 1, we performed tests to see whether removing these variables (post word count, reply word count, posts in period, number of replies to comments, and video posts) influenced results. For followers, image-based cues went from $p < .05$ to $p < .10$, as did competence cues. However, for positive interaction, image-based cues went from $p < .10$ to $p < .05$, and competence cues shifted from $p > .1$ to $p < .05$. However, these variables retained their original results when including solely posts in period, but omitting all the other control variables.

[25] Since HT requires time-variant and time-invariant variables, we were unable to employ it for this analysis; thus, we employed an ordinary least squares regression so we could omit the control variables.

LIWC. When using positive affect scores, we found that posts without emoticons and those with emoticons replaced by their text equivalent have a Cronbach's α of 0.99, signifying that the differences between measurements are minimal, and we are not missing substantial emotional sentiment by excluding the emoticons from our analysis.

Endogeneity. Finally, while the HT regressions we used for our main analyses alleviate concerns about endogeneity associated with a possible fixed effect (Hausman & Taylor, 1981), to rule out any further endogeneity concerns we also performed a robustness of inference to replacement (RIR) analysis, which is equivalent to an impact threshold of a confounding variable (ITCV) analysis, but is more appropriate for nonlinear models (Busenbark, Yue, Gamache, & Withers, 2022; Frank, Maroulis, Duong, & Kelcey, 2013). RIR and ITCV analyses allow researchers to determine how strong the effect of a particular variable would have to be to potentially create an endogeneity issue that overturns the findings (Busenbark et al., 2022; Frank, 2000). We employed the *konfound* command in Stata and assessed the effects of our four predictors on the two outcomes based on our Table 2 results.

For the number of followers, 69.02% of cases (2,013 cases) for word-based cues, 5.03% of cases (147 cases) for image-based cues, 15.94% of cases (465 cases) for competence-based cues, and 76.40% of cases (2,228 cases) for warmth-based cues would have to be biased to affect our results. For positive interactions, 50.46% of cases (1,471 cases) for word-based cues, 7.38% of cases (215 cases) for image-based cues, 46.26% of cases (1,349 cases) for competence-based cues, and 51.70% of cases (1,508 cases) for warmth-based cues would have to be biased to affect our results. Thus, only image-based cues may be a concern, but given our use of HT models and the extensive control variables we include, particularly with respect to images, it seems unlikely that an omitted variable would result in these levels of bias. As Busenbark and colleagues (2022) noted, if researchers cannot identify a plausible omitted variable, then even low percentages are not problematic. Thus, endogeneity does not appear to be an issue.

DISCUSSION

In this study we explored differences in how communicating using words and images, and the warmth and competence cues conveyed, influence the extent to which social media followers engage with influencers. We found that although image-based cues had a positive relationship with lower-level engagement (following) and word-based cues did not have a significant relationship, they did not differ in the magnitude of their effects. However, word-based cues had a significantly stronger relationship with higher-level engagement (positive interactions) than did image-based cues. Further, whereas competence cues had a stronger positive relationship with following than warmth cues, warmth cues had a positive, significant relationship with positive interactions, but competence cues did not. These findings have several theoretical and practical implications.

Theoretical Implications

Contributions to multimode communication. Our study contributes to multimodal communication research (e.g., Barberá-Tomás et al., 2019; Messaris, 1997; Meyer et al., 2018) by building on differences in images' and words' iconicity, indexicality, and syntactic determinacy (Messaris, 1997) to understand how they influence behaviors that require different amounts of cognitive effort. Prior multimodal communication research has tended to conflate communication mode and content (e.g., Barberá-Tomás et al., 2019; Fehrenbach & Rodogno, 2015; Geise & Baden, 2015; Jarvis et al., 2019), and has not considered how the cognitive effort associated with different engagement behaviors can shape the communication mode's relative influence. We argue that images' faster processing (Thorpe et al., 1996), ability to serve as "proof" something occurred (their indexicality) and its greater interpretive flexibility (syntactic indeterminacy) (Messaris, 1997) enhance their influence when little cognitive effort is required to motivate the engagement behavior. The greater cognitive effort required to interpret words make them less influential in this circumstance.

However, when a behavior requires greater cognitive effort, words' greater syntactic determinacy can provide the causal logic or create the trust necessary to motivate the action (Messaris, 1997), and images' strengths become less influential. Although we did not find a statistically significant difference in the magnitude of image- and word-based cues' effects on lower-level engagement behavior, despite words not having a statistically significant relationship with this behavior, this may have been due to the large confidence intervals for these measures with respect to followers, or to combining images and words with different content cues. However, the patterns of statistical significance do provide some evidence to support our contentions, and our arguments were supported for high-level engagement behaviors. Future research should continue to explore the different influences images and words can have in other contexts.

The Big-Two information cues and social judgments. Prior research on warmth and competence cues has generally found that although both are important, warmth plays a greater role than competence in shaping social judgments (Abele & Wojciszke, 2014; Fiske et al., 2007). However, these studies have not expressly considered the cognitive effort the behavior taken requires, and whether the type of cue matches the motivations required to make the necessary cognitive effort. We contribute to this literature by theorizing and showing that the receiver's goals and the amount of cognitive effort a particular engagement behavior entails can lead to differences in which type of cue is more influential. We found support for our argument that assessing competence was more influential on lower-level engagement behaviors that require less cognitive effort, and that in these circumstances the sender needs to demonstrate that they possess the necessary ability, and not just that they are likable. In contrast, warmth cues are more influential in motivating more cognitively effortful higher-level engagement behaviors, where the ability to stimulate perceptions of trust, authenticity, and likeability are more important. Further, our *post hoc* analyses showed that the modes through which these cues are conveyed can also affect their influence. Future research should give greater theoretical attention to both the behaviors the cues are motivating and the modes through which they are conveyed.

Our *post hoc* tests also provide some additional insights. While image-based competence cues had a significant relationship with low-level engagement and image-based warmth cues did not, image-based warmth cues had a significant relationship with high-level engagement behaviors and image-based competence cues did not. Further, word-based warmth cues had a negative, significant relationship with low-level engagement behaviors, but a positive, significant relationship with higher-level engagement behaviors. Indeed, image-based competence cues had the greatest positive influence on lower-level engagement, and word-based warmth cues had the greatest influence on higher-level engagement. This is consistent with our argument that competence and warmth cues motivate different levels of cognitive effort, even when conveyed through the same mode. This is illustrated further when looking at the use of contrasting cues (imaged-based competence cues with word-based warmth cues, and vice versa).

These findings illustrate that the differences in cognitive effort individuals are willing to expend depends on both the communication mode and the communication's content, and that warmth cues, whether conveyed through images or words, can help establish the influencer's trustworthiness and authenticity, and are more influential in motiving higher-level engagement. Future research in other contexts and using alternative measures should continue to theorize how varying mode–content combinations affect different levels of engagement.

Entrepreneur–stakeholder engagement. While prior research has stressed the importance of stakeholder engagement (Desai, 2018), it has primarily focused on the dyad level, providing key insights on one-to-one interactions—for example, manager–employee engagement, employee–employee engagement, firm–firm engagement, or even customer–employee engagement (Cardador & Pratt, 2018; Rodell, Sabey, & Rogers, 2020; Zablah, Carlson, Donavan, Maxham, & Brown, 2016). However, our understanding of how a single individual or firm can engage with many different stakeholders simultaneously, especially in the earlier stages of their ventures' life cycles, is more limited (entrepreneur to investor groups is a notable exception). On social media, a single individual can persuade numerous (sometimes hundreds of thousands or more) followers to engage with them. We contribute to understanding entrepreneur–stakeholder engagement by theorizing how individual actors can employ different communication modes and cues to motivate different behaviors, and by considering how they relate to the mechanisms that affect customer engagement (van Doorn et al., 2010). Future research should continue to explore these dynamics.

Practical Implications

Our study also has practical implications, whether they are employed by social media influencers, entrepreneurs using social media or other online means to promote their businesses, or nonprofits seeking to generate different types of engagement. Our results show how actors can employ images and videos that demonstrate their competence to motivate lower-level engagement, such as enhancing their following. They can also provide word-based evidence of their competence, and both image- and word-based warmth cues to increase higher-level engagement behaviors, such as stimulating positive interactions, or promoting the actor to others. They should avoid self-focused rhetoric (e.g., "I'm so stoked

I hit my personal best in the squat") or general cheerleading (e.g., "This new protein powder rocks!"), and instead employ rhetoric that focuses on the stakeholders they are trying to engage (e.g., "I'm so proud of Jessica for hitting her bench press goal. Way to crush it!"). More effectively motivating both types of engagement can create additional monetization opportunities (e.g., brand expansion opportunities, third-party endorsements). Social media posts do not have to be long, but interacting regularly and showing that they are paying attention to followers is crucial for establishing an online relationship and encouraging high-level engagement behaviors.

Limitations and Future Research

Like any study, ours has limitations that suggest future research directions. First, just as we advise caution in generalizing theory developed in offline contexts to social media, we must be cautious in generalizing our findings outside the social media context. While images are important in the business-to-consumer (B2C) fitness and nutrition industry, and should theoretically be important for all industries where it is vital to see a product (e.g., consumer goods, new technologies) or showcase unobservable qualities, (e.g., service-based ventures such grooming, consulting, or cooking), images may not have the same impact as our findings demonstrate. Even online, the dynamics we observed might not hold in business-to-business relationships, or B2C contexts where visual evidence is less dramatic. However, given the rapid increase in online retail sales—14.9% versus 3.8% for total retail sales between 2018 and 2019 (U.S. Department of Commerce, 2019)—understanding whether and how the dynamics we have identified play out in these other online contexts is an interesting avenue for future research. Context also plays an important role in assessing the implications of effect sizes. Finding any effect, especially when including highly correlated controls, or with variables that have small variations, can be consequential (Cortina & Landis, 2009). Given the large followership distributions on social media, for some influencers even seemingly small effect sizes can result in significant increases in followers. Future research should account for this when studying social media.

Second, our research design suggests future research opportunities. Because we collected data over a specific time period we compared entrepreneurs at different phases of development. Given (a) our sample's relative maturity, (b) the fact that monthly followership changes averaged just 1.5%, and (c) the fact that many of the independent variables had minimal monthly changes, we were unable to compare within-influencer changes month over month. Future research taking a longitudinal approach using samples that track entrepreneurs from founding onwards could expand on these preliminary findings, and enhance our understanding of how influencers begin engaging followers, and whether and how this process changes over time as their followership grows. This is especially important given that social media engagement is a dynamic environment, where "engagement … may emerge at different levels of intensity over time, thus reflecting distinct engagement states" (Brodie, Ilic, Juric, & Hollebeek, 2013: 105). Future studies could also allow for a more robust understanding by using more granular measures of image-based cues, given that some images also contain words. Instagram does not publicly indicate it uses image content in its placement algorithm (Cooper, 2019), but advances in machine learning could make this possible in the future.

Finally, while prior research on startup funding has focused on traditional credentials' influence on investors' decision-making (e.g., Chen, Yao, & Kotha, 2009; Hallen, 2008), scholars should further explore how image-based competence cues affect investors' actions. For example, crowdfunding only allows for computer-mediated communication, and both image- and word-based competence cues are used to persuade investors (Davis, Hmieleski, Webb, & Combs, 2017; Mahmood, Luffarelli, & Mukesh, 2019). Further understanding the role that multimodal communication plays in various funding situations can help researchers better understand other contexts where entrepreneurs are attempting to drive stakeholder behaviors.

CONCLUSION

Entrepreneurs can persuade stakeholders to engage with them through a variety of means. By studying entrepreneurs on the social media platform Instagram, we were able to expand our knowledge about the range of modes (images and words) and content cues (warmth and competence) that influence stakeholders' engagement behaviors. Thus, while our opening quote was (mostly) in jest, for social media influencers having abs may indeed be enough to increase followership, but it is not enough to get followers to positively interact with them.

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