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A content-based metric for social media influencer marketing

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Abstract

Purpose – The study aims to propose an instrument for measuring product-centeredness (i.e. the extent to which comment content is related to a product) using word embedding techniques as well as explore its determinants.

Design/methodology/approach – The study collected branded posts from 205 Instagram influencers and empirically examined how four factors (i.e. authenticity, vividness, coolness and influencer–product congruence) influence the content of the comments on branded posts.

Findings – Post authenticity and congruence are shown to have positive effects on product-centeredness. The interaction between coolness and authenticity is also significant. The number of comments or likes on branded posts is not correlated with product-centeredness.

Originality/value – In social media influencer marketing, volume-based metrics such as the numbers of likes and comments have been researched and applied extensively. However, content-based metrics are urgently needed, as fans may ignore brands and focus on influencers. The proposed instrument for assessing comment content enables marketers to construct content-based metrics. Additionally, the authors' findings enhance the understanding of social media users' engagement behaviors.

Keywords Social media influencers, Influencer marketing, Word embeddings, Comment content, Instagram

Paper type Research paper

1. Introduction

In recent years, brands have constantly communicated and interacted with consumers via social networking sites. In social media marketing, one of the most widely used strategies is influencer marketing (Geng *et al.*, 2020). Influencers are social media users who have received significant attention from other users and gained a sizable network of followers (Farivar *et al.*, 2021). Influencer marketing refers to the collaboration of businesses with social media influencers to promote brands and products through the influencer's social media (Farivar *et al.*, 2021). Specifically, influencers endorse a product or service by creating posts on their social media accounts to promote the brand. Furthermore, influencers and branded post viewers can interact in the comment section such as leaving comments on the product, which increases viewers' engagement with the brand. Further, these comments enable firms to better understand customers and increase products (McCorquodale, 2020).

Given the growing popularity of influencer marketing, a significant challenge arises for marketers: how to properly evaluate the performance of influencer marketing. Recent surveys show that the most frequently employed performance metrics in influencer

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marketing practice are counts and engagement rates such as the numbers of likes and comments on posts or the sum of like and comment counts divided by follower count (Gräve, 2019; Linqia, 2020). In the influencer marketing literature, like, comment and share counts are also typically used as performance outcomes by researchers (Tafesse and Wood, 2021).

However, recent research has found that volume-based metrics may only partially reflect the performance of marketing campaigns (Gräve, 2019). Scholars have emphasized that marketers should keep track of not only like and comment counts but also comment content (Lou *et al.*, 2019) and called for more research on content-based metrics (Gräve, 2019). Furthermore, as Hartmann *et al.* (2021) noted, fans may pay most of their attention to the influencer and ignore the product presented on branded posts. As such, it is essential to detect comment topics. If the focal topic of comment content is product-related (i.e. a product-centered comment), it explicitly indicates that the product has received attention from viewers.

In the era of big data, an influencer's post may receive hundreds of comments. To determine how closely comment content is related to a product or brand, marketers must read comments and judge the content. It is a challenge for marketers to manually analyze a large amount of data, which discourages firms from adopting content-based metrics. The first aim of the present study is to address this issue. We propose an instrument for measuring the extent to which comment content is related to a product (i.e. product-centeredness) by using automatic text analysis tools, thus enabling marketers to apply content-based metrics to influencer marketing programs readily and efficiently.

In addition to detecting whether comment content is product-centered, prompting viewers to discuss products is crucial for firms. First, research has indicated that social media users read not only influencers' posts but also the comments written by other users (Qin, 2020). Thus, when post viewers write more product-centered comments, firms gain wider brand exposure in social media. Second, product-centered comments reflect viewers' interests and concerns and can thus be used to improve product performance effectively (Lou *et al.*, 2019). For example, Juliana Salimeni, a Brazilian social media influencer, endorsed a hair dye brand on Instagram (Silva *et al.*, 2020). In the comment section, her post's viewers shared their product-related experience. One of the comments stated, "I use Gold but why does my hair look green?" The comment clearly signifies that actions such as a thorough inspection of product quality must be taken.

Despite the significance of comment content in influencer marketing, the factors affecting comment content remain underexplored in the literature. The second aim of this study is exploring factors that may drive post viewers to comment on a product or brand. According to the affective-cognitive model, individuals' decision-making is affected by cognitive and affective information processing (Berkowitz, 1993; Shiv and Fedorikhin, 1999). Numerous studies adopt this model to explore how advertising messages and word-of-mouth influence social media users (Li and Huang, 2020; Zhang and Lee, 2022). Our research also builds on this theoretical framework. We investigate the effects of cognitive factors (i.e. the authenticity and congruence between influencer and product) and affective factors (i.e. vividness and coolness) on product-centeredness. Our findings contribute to the body of knowledge on social influencer marketing and offer useful implications to enhance marketing effectiveness.

2. Theoretical background and hypotheses development

2.1 Product-centeredness in comment content

Social media users can interact with influencers and other users through actions such as liking, commenting and sharing (Song and Park, 2020). Compared with clicking on the "Like" button, commenting involves stronger self-presentation on social media, as users can deliver more complicated messages by commenting on online posts. Recently, topics of comment content have been given increasing scholarly attention. Studies have found that branded posts' comments can be categorized into two primary types, namely influencer- and product-centered comments (Lou *et al.*, 2019; Silva *et al.*, 2020). In influencer-centered comments, fans discuss influencers' beauty or lifestyles and express their admiration.

The other primary comment topic is the product or brand. In product-centered comments, fans show their feelings or love for products (i.e. product attitude), product use experiences (i.e. word-of-mouth) and desire for products (i.e. purchase intention) (Lou *et al.*, 2019; Silva *et al.*, 2020). The comments exhibiting purchase interests (e.g. "I want to get one") are a direct reflection of the effectiveness of influencer marketing. Furthermore, commenters may discuss specific product features such as functions, appearance and performance or express their complaints or concerns regarding the product. Product-centered comments echo the branded post and provide additional or supplemental information on the product (Lou *et al.*, 2019; Silva *et al.*, 2020). To date, the factors that motivate fans or viewers to comment on a product remain unclear. Drawing on the literature, this study explores the factors that influence product-centeredness in comment content.

2.2 Affective-cognitive model

The affective-cognitive model is one of the key theories to explain decision-making and behavioral processes (Berkowitz, 1993; Shiv and Fedorikhin, 1999). The model postulates that individuals' decisions are affected by affective and cognitive processing. Affective processing, which stresses the role of feelings, tends to occur relatively automatically (i.e. lower-order processing). Such processing can arouse affective reactions even when individuals' processing resources for decision-making are limited. By contrast, cognitive processing involved in thinking, reasoning, and consciousness is more deliberative and controlled (i.e. higher-order processing). Prior research has demonstrated that consumers' judgment is shaped by both cognitive and affective reactions (Li and Huang, 2020; Zhang and Lee, 2022). Furthermore, the model suggests that when processing resources are sufficient, individuals' final decisions are primarily affected by higher-order cognitive processing. Cognitive processing can strengthen or weaken the reactions elicited by affective processing (Berkowitz, 1993). However, when processing resources are inadequate, affective processing can be more influential over decision-making.

The affective-cognitive model has been widely used by prior studies to interpret social media users' behaviors (Li and Huang, 2020; Zhang and Lee, 2022). From the same theoretical perspective, this study identifies potential determinants of product-centeredness. Authenticity and congruence between influencer and product are included as the cognitive factors affecting product-centeredness in this study. Prior research has found that these two factors, which require viewers' cognitive processing to make judgment such as reasoning, significantly influence the effectiveness of influencer marketing. For example, when authenticity in a branded post is high, followers' purchase intention increases (Zafar *et al.*, 2021). Further, congruence has been shown to positively affect viewers' attitudes toward a product (Kim and Kim, 2021a). We believe that not only viewers' attitudes toward a product but also their comments on a product are influenced by authenticity and congruence.

In addition to cognitive stimuli, affective stimuli (e.g. attractiveness or esthetic appeal) that trigger sensory pleasure can increase social media users' engagement (Zhang and Lee, 2022). This study also explores the impact of affective factors (i.e. vividness and coolness) on product-centeredness. First, vividness is the degree of sensory stimulation caused by content (Steuer, 1992). Previous research has shown that branded posts with high vividness increase viewers' purchase intention and interactions between followers and the brand (Chandrasekaran *et al.*, 2019; Colicev *et al.*, 2019). Second, coolness is associated with being fashionable, amazing, unique and attractive (Rahman, 2013). Research has found that perceived coolness significantly promotes the diffusion of brand word-of-mouth (Bagozzi and Khoshnevis, 2023). This study examines the direct effects of vividness and coolness on product-centeredness as well as their interactions with authenticity.

The post characteristics (i.e. authenticity, vividness and coolness) are highly relevant to influencer marketing. As AlRabiah *et al.* (2022) pointed out, a social media influencer's branded posts are essentially electronic word-of-mouth, the characteristic of which is that influencers disclose their real or personal life with fans. Thus, authenticity is crucial in influencer marketing. Additionally, vividness and coolness could make branded posts more appealing. Research has shown that attention-grabbing (e.g. posting eye-catching images) is a key rhetorical tactic that influencers employ when they create electronic word-of-mouth (Zhou *et al.*, 2021). As for the congruence between influencer and product, it is a variable that directly relates to the social media influencer. Exploring the influence of these factors will provide practical implications for marketers to perform social media influencer marketing.

2.3 Authenticity

In the literature on digital marketing, authenticity has become a main research topic. In general, authenticity refers to what is genuine, real and true (Kowalczyk and Pounders, 2016). Post authenticity is defined as a post or photo that demonstrates some aspects of a celebrity's true self (Kowalczyk and Pounders, 2016). Different from the authenticity that represents an influencer's personal qualities (Kim and Kim, 2021b), post authenticity is a post characteristic. Since our study focuses on branded posts, authenticity is defined here as the extent to which an influencer's positive feelings toward a product or usage experience are genuinely presented in a post. A highly authentic post contains informative clues about influencers' positive feelings or experiences with products.

Nanne *et al.* (2021) found that viewers demonstrate more favorable attitudes toward a product in a branded post when the post sender is holding the product with a smile compared with a branded post where the sender displays a neutral facial expression. Because a smile provides more clues about the sender's true feelings toward the product, it is easier for viewers to infer that the sender is enjoying the product, thereby influencing viewers' attitudes toward the product.

Hwang and Zhang (2018) found that a branded message sent by a digital celebrity with persuasive or selling attempts inhibits followers' intention to favorably talk about the brand. However, this inhibitory effect can be alleviated when fans believe that the brand satisfies the celebrity's need. Accordingly, since highly authentic posts foster viewers' inference that an influencer genuinely loves the endorsed brand, viewers' resistance to generating electronic word-of-mouth would be mitigated. Moreover, Martínez-López *et al.* (2020) found that credible and believable posts can increase viewers' interest in the endorsed product and information-seeking behavior, which may prompt product-centeredness (e.g. asking questions about the product in the comment section). As such, a product in a highly authentic post is more likely to be a comment topic than one in a less authentic post. Hence, we hypothesize:

H1. The higher the authenticity of a branded post is, the more product-centered the content of the comments on the post is.

2.4 Congruence

In influencer marketing, influencer–product congruence is an important factor determining the effectiveness of sponsored posts (Schouten *et al.*, 2020). Congruence refers to the degree of similarity between two entities or activities (Olson and Thjømøe, 2011). For example, influencer–product congruence is high when a beauty blogger endorses a tinted moisturizer, whereas the congruence between a beauty blogger and a protein shake is low (Schouten *et al.*, 2020). Previous research has shown that influencer–product congruence is positively associated with users' attitudes toward influencer, influencer credibility and products (Breves *et al.*, 2019). Yet, it remains unknown how influencer–product congruence affects comment content.

Apart from attitudes and preferences, people draw inferences about the motives of others (Aw and Chuah, 2021). When a brand and an influencer are highly congruent, viewers tend to infer that the reasons for sharing a post mentioning a brand are the influencer's emotional bond with the brand and the importance of the brand to the influencer (Kim and Kim, 2021a). In other words, high influencer–product congruence leads to affective motive inference, making viewers think that the influencer has genuine fondness for the brand. A brand or product is therefore more likely to be discussed by fans (Hwang and Zhang, 2018). Hence, we hypothesize:

H2. The higher the influencer–product congruence of a branded post is, the more product-centered the content of the comments on the post is.

2.5 Vividness

Vividness refers to the representational richness of a mediated environment, as defined by its formal features, that is, the way in which an environment presents information to the senses (Steuer, 1992). Yoo and Kim (2014) found that vividness can induce a series of events in viewers' minds of which they were a part. In other words, information recipients can live this experience in their minds as if they have immersed themselves in it. Furthermore, people experience a sense of presence or proximity across senses, time and space when encountering vivid information (Steuer, 1992).

Extant research has indicated that vividness enhances brand consideration and purchase intention among social media users (Colicev *et al.*, 2019). Vivid branded posts that highlight products can strongly stimulate viewers' senses and give viewers more engaging brand experiences. It is common that the focus of a branded post is an influencer's product usage experience such as a photo showing that a lotion is being applied by a beauty influencer. When a branded post is highly vivid (e.g. clear or rich in detail), viewers may feel as if they are really using the featured product together with the influencer, thereby driving them to be more likely to talk about the brand. Hence, we posit:

H3. The higher the vividness of a branded post is, the more product-centered the content of the comments on the post is.

2.6 Coolness

Coolness plays a significant role in social media usage behavior. For example, one of the primary motivations of using Instagram is coolness (Sheldon and Bryant, 2016). Coolness is generally considered to be a positive and desirable quality associated with being original, unique and innovative (Liu and Mattila, 2019). The concept of coolness is widely used in marketing. Previous studies have found that consumers' attitudes toward brands, new products and services are influenced by how "cool" these are (Im *et al.*, 2015; Liu and Mattila, 2019).

Cool objects spark interest, excitement, joy and pleasure for people (Im *et al.*, 2015). Prior research has indicated that experiencing awe from viewing video advertisements elicits people's needs or desires to talk or create fun interactions with friends (Nikolinakou and King, 2018). Furthermore, perceived coolness drives consumers to share their views on a brand (Bagozzi and Khoshnevis, 2023). Another study found that uniqueness, a key element of coolness, significantly encourages brand conversations (Bastos and Brucks, 2017). Hence, we hypothesize:

H4. The higher the coolness of a branded post is, the more product-centered the content of the comments on the post is.

2.7 Interaction of authenticity with coolness and vividness

Authenticity, vividness and coolness are post characteristics. Different post-related factors may interplay with each other. According to the persuasion knowledge model, once individuals identify a persuasive attempt, their resistance to persuasive content is likely to rise (Friestad and Wright, 1994). In a less authentic branded post, while the product is featured, clues about the influencer's true feelings and usage experience are scarce. Thus, the post seems to be a form of advertising. Research has indicated that an advertiser's salient ulterior motive or intent to manipulate leads to persuasion knowledge activation (Campbell and Kirmani, 2000). As such, when post authenticity is low, viewers' persuasion knowledge is likely to be activated. Prior research has found that excessively prominent product placement (i.e. lower authenticity) in social media posts raises viewers' suspicion that the influencer has not actually bought or used the product (Cárdaba *et al.*, 2023).

Research has shown that followers' intention of talking about products on influencers' posts is hindered when persuasion knowledge is activated (Hwang and Zhang, 2018). Therefore, it can be expected that when authenticity is low, viewers' desire and willingness to discuss a brand and product induced by high vividness or coolness may be inhibited. In other words, for low authenticity, the positive effects of vividness or coolness on product-centeredness might be weakened. By contrast, the effect of persuasion knowledge is less salient for highly authentic posts, meaning the influence of vividness and coolness could be exerted more strongly. Hence, we posit:

H5. The effect of vividness on product-centeredness is stronger when the authenticity of a branded post is high.

H6. The effect of coolness on product-centeredness is stronger when the authenticity of a branded post is high.

3. Research design

To address the two objectives of this study, we first propose and validate a method for measuring product-centeredness and then examine its determinants.

3.1 Proposed instrument for measuring product-centeredness

This study proposes a product-centered score (PCS) as the instrument to measure product-centeredness by applying word embedding techniques.

3.1.1 Word embeddings. Word embeddings, also known as distributed word representations, represent words with dense, low-dimensional and real-valued vectors (Wang *et al.*, 2016). Each dimension of a vector represents a different aspect of a word. In the embedding space, semantically related words are usually closer to each other. Recently, neural network language models such as the continuous bag-of-words have been used to learn high-quality word embeddings (Bojanowski *et al.*, 2017).

The goal of training a continuous bag-of-words model is for it to learn to predict word representations based on a given context. Since the model takes co-occurrent information into consideration, some words that often appear in similar contexts have closer vector representations (Bojanowski *et al.*, 2017). For example, "dessert" generally appears more frequently in the same context as "delicious" than "handsome" does. According to the vector of these three words provided by fastText, a pre-trained word embedding technique based on the continuous bag-of-words model, we calculated the cosine similarity between them to measure their degree of similarity. The cosine similarity between "dessert" and "delicious" is 0.59, whereas the similarity value between "dessert" and "handsome" is 0.14.

3.1.2 Calculation of the PCS. Word embedding techniques are widely employed in social media research (Grzeça *et al.*, 2020; Lindow *et al.*, 2021). One application of word embeddings is detecting a given topic or theme in user-generated content. For example, Lindow *et al.* (2021) measured the fear expressed in tweets during the outbreak of the novel coronavirus disease by computing the cosine similarity between tweets and fear-related words. In this study, the PCS measures the association between comment content and a given product (represented by a product-category word) via word embeddings.

Before calculating the PCS, the vector representation of each comment must be created. In prior social media research, scholars have generated a vector of a given tweet by averaging the vector values of all the words in the tweet (Grzeça *et al.*, 2020). A detailed illustration of the calculation is shown in Grzeça *et al.* (2020, p. 7). Following prior research, we employ the averages of word vectors to obtain the vector representation of an Instagram comment. For instance, a post sponsored by a juice brand receives two comments: "lovely smile" and "refreshing flavor." Table 1 shows the computation of the two comment vectors. Extant research has shown that this method performs satisfactorily for different natural language process tasks (Kenter *et al.*, 2016). After obtaining the vectors of all the comments, we can calculate the PCS of a branded post.

The PCS is calculated as described below. First, we determine a product-category word for the product in a branded post and obtain its word vector. Second, the similarity between a comment and the product-category word is computed. This similarity value is called the comment PCS. Consistent with prior research (Lindow *et al.*, 2021), we adopt cosine similarity as a measure of similarity. The calculation is as follows:

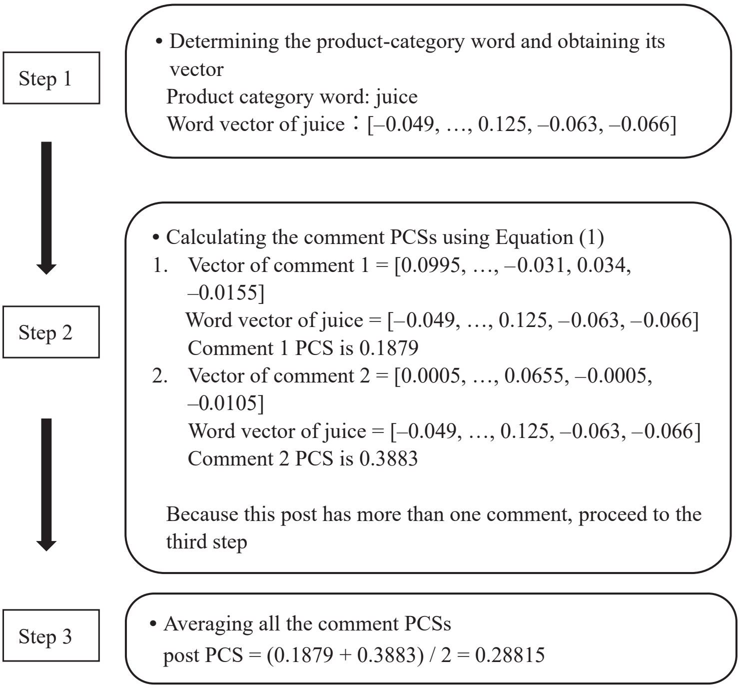
$$\frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=i}^{n} B_i^2}} \tag{1}$$

A_i and B_i denote the elements of the product-category word vector and comment vector, respectively. If a post has only one comment, its comment PCS is the PCS of the branded post (post PCS). Third, for a post with more than one comment, we average all the comment PCSs obtained in step 2 to generate the PCS of the post. The calculation of the post PCS for the example in Table 1 is illustrated in Figure 1. Since the value of cosine similarity ranges from

Word	1	...	Dimension 298	299	300
Comment 1					
Lovely	0.045		−0.011	−0.003	0.004
Smile	0.154		−0.051	0.071	−0.035
Average	0.0995a		−0.031	0.034	−0.0155
Vector of comment 1 = [0.0995, . . ., −0.031, 0.034, −0.0155]					
[a](0.045 + 0.154)/2 = 0.0995					
Comment 2					
Refreshing	0.004		0.014	0.027	−0.004
Flavor	−0.003		0.117	−0.028	−0.017
Average	0.0005		0.0655	−0.0005	−0.0105
Vector of comment 2 = [0.0005, . . ., 0.0655, −0.0005, −0.0105]					

Note(s): The word vectors of "lovely," "smile," "refreshing" and "flavor" are taken from fastText and each word vector has 300 dimensions

Table 1. Example of the calculation for the comment vectors



Note(s): The word vector of "juice" is taken from fastText and has 300 dimensions

Figure 1.
Example of the post PCS calculation

-1 to 1, the post PCS also lies within this range. The closer the post PCS is to 1, the higher is the similarity between the comment content and product-category word. When the post's PCS is higher, the content of its comments is considered to be more product-centered.

3.1.3 Validation. To evaluate the concurrent validity of the PCS, this study adopted an approach used for evaluating automatic text analysis tools in previous studies. Past research has compared the results of text analysis between human raters and automatic analysis tools to assess validity (Hagen, 2018). We collected 419 comments written in Chinese from Instagram branded posts. Instagram was founded in 2010, being currently one of the most influential social networking platforms. The product-category words were determined based on the product image in the photos as well as the text in the captions. Using the steps mentioned above, comment PCSs were then calculated for the comparison.

In this study, word vectors were obtained using fastText (Grave *et al.*, 2018). It provides pre-trained models in 157 languages (see https://fasttext.cc/docs/en/crawl-vectors.html). We thus utilized fastText Chinese word embeddings with 300 dimensions. Some of the comments contained numbers, emoticons, emojis and punctuation marks. Further, some nouns such as influencers' nicknames were not included in the fastText pre-trained model. Hence, there were no word vectors for them. We removed these elements before calculating the PCS. Furthermore, we excluded stop words from the comments. Stop words are common words (e.g. "I" and "your") and function words (e.g. "is" and "the") that include little semantic information. Thereafter, two human raters (rater A and rater B) were recruited and trained for the analysis. They independently viewed the posts and read the comments. They then rated the comments on a five-point scale, where 0 indicates that the comment is not relevant to the product and 5 indicates high relevance. Inter-rater reliability (i.e. the coefficient of correlation between the two human raters) is 0.912.

The study subsequently compared the comment PCSs with the results of the human ratings. Correlation analyses were conducted. The results show that the coefficient of correlation between the comment PCSs and scores from rater A (B) is 0.756 (0.811). The coefficients indicate a highly significant positive correlation between the human ratings and comment PCSs [1]. The results indicate acceptable validity.

3.2 Data collection

The posts used in our analyses regarding the contributing factors of product-centeredness were obtained from Instagram. These posts were uploaded by influencers in Taiwan. The captions and comments were written in Chinese. Along with the photos and captions, we also collected profile information, hashtags, date of posting, like count, comment count and follower count.

The selection of branded posts was based on the following criteria. First, Instagram enables users who have above 10,000 followers to use certain exclusive features (e.g. swipe up). We adopted this criterion to select Instagram influencers. Additionally, celebrities such as actors, singers and sports stars were excluded from the analysis. Second, since our study focuses on branded posts from influencers, we only chose those posts revealing collaborations or sponsorships with brands. Initially, we selected branded posts from 500 influencers' accounts. The posts were included in our sample. Next, only those posts with photos that show both the influencer and the brand were kept.

Regarding the product category of the branded posts, five categories (i.e. beverages, cosmetics, food, apparel and accessories and consumer electronics) were chosen. Since well-known brands such as Coca-Cola and McDonald's may attract stronger interest from post viewers, we screened all the brands in the dataset and excluded those ranked within the top 50 valuable brands (Forbes, 2021). Lastly, we checked the profile sections of the influencers' accounts. If an influencer's profile information did not clearly reveal occupation (e.g. chef) or domains of interest (e.g. beauty, cooking, or gaming), the influencer's post was removed from the sample. Based on this, a final sample of 205 influencers' posts was used for analysis. In total, 43.4% are male. The numbers of the product categories (i.e. beverages, cosmetics, food, apparel and electronics) are 55, 48, 44, 30 and 28, respectively. Summary statistics are provided in Table 2.

Variable	Mean	SD	Min.	Max.
Follower count	43298.302	42086.468	10,026	285,037
Like count	1503.161	1681.485	78	12,722
Comment count	16.336	16.119	1	103
PCS	0.268	0.076	0.096	0.773
				Frequency(percentage)
Authenticity				92 (44.9)
Vividness				86 (42.0)
Coolness				99 (48.3)
Congruence				107 (52.2)
Product-centeredness				81 (39.5)

Table 2.
Summary statistics of the sample posts

4. Analysis and results

4.1 Data coding

To test the proposed hypotheses, the data were first coded using a coding scheme developed in prior research on social media (Gavilan *et al.*, 2020). Afterward, regression analysis was conducted. Based on previous studies, we developed a coding sheet and listed the criteria for evaluating the variables. For example, regarding authenticity, when products are presented as part of influencers' real lives in their posts, a post is perceived as more authentic (Audrezet *et al.*, 2020). Moreover, facial expressions are critical visible indications of a branded post sender's true feelings about a product (Nanne *et al.*, 2021). Table 3 lists the coding criteria for the variables.

After finalizing the coding criteria, this study invited two experts as human coders. Coder A is a marketing manager with seven years of experience in social media and digital marketing and coder B is a professor at a business school. After being fully informed of the criteria, the coders carefully viewed each post (including photos, caption, profile information and comments) and evaluated the posts independently. All variables were binary-coded, where 1 indicates that the variable is present and 0 indicates that the variable is absent. We compared the coding results and marked any discrepancies. Concerning the inconsistent results, the two coders had face-to-face discussions until consensus was reached. Finally, a post was categorized as high product-centeredness when more than half of its comments were coded as product-centered. Table 4 shows the correlation matrix of the variables.

Variable	Characteristics for consideration	References
Authenticity	• Using the product in real life; emotional verbal information • Facial expressions	Audrezet *et al.* (2020) and Nanne *et al.* (2021)
Vividness	• Being attention catching, clear, exciting, and detailed • Concrete verbal information or background	Mandler *et al.* (2020) and Yoo and Kim (2014)
Coolness	• Being fashionable, amazing, unique, and sophisticated	Rahman (2013)
Congruence	• A match between a product and an influencer's profession or interests	Schouten *et al.* (2020)
Product-centeredness	• Comment content is related to a product	Lou *et al.* (2019) and Silva *et al.* (2020)

Table 3.
Coding criteria

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) Authenticity	1					
(2) Vividness	0.187	1				
(3) Coolness	0.011	0.029	1			
(4) Congruence	0.039	0.121	0.163	1		
(5) Product-centeredness	0.394	0.041	0.078	0.194	1	
(6) PCS	0.323	0.001	0.056	0.155	0.412	1

Note(s): Product-centeredness is the dependent variable for the logistic regression; PCS is the dependent variable for the OLS regression

Table 4.
Correlation matrix of the variables

4.2 Regression analysis

This study implemented a binary logistic regression analysis to test the hypotheses. The influencer's gender, follower count, product category, days since published and word count of the caption were included in the model as control variables. Because the distribution of follower count was skewed, the data were log-transformed. The results showed that all the variance inflation factors were below 3.12, meaning multicollinearity is not a serious concern.

Table 5 presents the results of the regression analysis. As shown in Model 1, authenticity is positively and significantly related to product-centeredness ($\beta = 1.832, p < 0.01$; see Model 1 in Table 5); therefore, the result supports H1. Moreover, congruence has a positive and significant relationship with product-centeredness ($\beta = 0.847, p < 0.05$). Therefore, H2 is supported. There are no significant main effects of coolness or vividness on product-centeredness. H3 and H4 are thus not supported. Similarly, Model 2 shows that authenticity and congruence are positively associated with product-centeredness.

As reported in Model 2, the interaction term between authenticity and vividness is non-significant for product-centeredness. Therefore, H5 is not supported. However, the interaction term between authenticity and coolness for product-centeredness is significant and positive ($\beta = 1.561, p < 0.05$). H6 is supported.

To validate our conclusions, we conducted an ordinary least squares (OLS) regression analysis. The PCS was the dependent variable. The PCSs of the 205 branded posts were calculated. The product-category words of the posts are presented in the Appendix (Table A1). The results of the OLS regression analysis (see Table 6) are consistent with the hypothesis testing results from the binary logistic regression. Thus, H1, H2 and H6 are confirmed.

4.3 Supplementary analysis

Understanding the associations between metrics is crucial for developing an appropriate metric system; therefore, we performed a supplementary analysis. Independent sample *t*-tests

	Dependent variable: product-centeredness			
	Model 1		Model 2	
Independent variable	β (SE)	*p*-value	β (SE)	*p*-value
Intercept	−2.366 (2.415)	0.327	−2.246 (2.529)	0.375
Follower count	0.012 (0.513)	0.981	−0.060 (0.531)	0.910
Caption word count	0.042 (0.171)	0.805	0.025 (0.175)	0.887
Days of being posted[a]	−0.206 (1.76)	0.241	−0.258 (0.184)	0.161
Gender	0.197 (0.339)	0.560	0.256 (0.348)	0.462
Product category[b]				
Beverage	0.353 (0.548)	0.519	0.256 (0.564)	0.650
Food	0.440 (0.574)	0.444	0.432 (0.592)	0.466
Cosmetics	0.673 (0.566)	0.234	0.624 (0.579)	0.282
Electronics	0.498 (0.618)	0.421	0.479 (0.636)	0.451
Authenticity	1.832 (0.347)	0.000	1.298 (0.525)	0.013
Vividness	−0.322 (0.345)	0.351	−0.110 (0.494)	0.824
Coolness	0.327 (0.343)	0.340	−0.431 (0.485)	0.375
Congruence	0.847 (0.354)	0.017	0.796 (0.395)	0.027
Authenticity × Vividness			−0.464 (0.681)	0.496
Authenticity × Coolness			1.561 (0.677)	0.021
Nagelkerke *R*-square	0.265		0.295	

Note(s): [a]The number of days from the date of posting to the date of collecting
[b]Apparel, reference category

Table 5.
Results of the logistic regression model

Independent variable	Model 1 Estimate (SE)	Model 1 p-value	Model 2 Estimate (SE)	Model 2 p-value
	Dependent variable: PCS			
Intercept	0.312 (0.072)	0.000	0.307 (0.072)	0.000
Follower count	−0.019 (0.015)	0.211	−0.016 (0.015)	0.284
Caption word count	0.007 (0.005)	0.186	0.007 (0.005)	0.182
Days of being posted[a]	0.009 (0.005)	0.069	0.008 (0.005)	0.111
Gender	0.010 (0.010)	0.326	0.011 (0.010)	0.271
Product category[b]				
Beverage	−0.006 (0.017)	0.737	−0.010 (0.016)	0.561
Food	0.011 (0.017)	0.519	0.011 (0.017)	0.524
Cosmetics	0.004 (0.017)	0.807	0.004 (0.017)	0.830
Electronics	0.043 (0.019)	0.025	0.043 (0.019)	0.024
Authenticity	0.046 (0.011)	0.000	0.037 (0.016)	0.026
Vividness	−0.018 (0.010)	0.092	−0.005 (0.014)	0.732
Coolness	0.001 (0.010)	0.939	−0.018 (0.014)	0.191
Congruence	0.033 (0.011)	0.003	0.030 (0.011)	0.005
Authenticity × Vividness			−0.030 (0.020)	0.140
Authenticity × Coolness			0.046 (0.020)	0.022
F-value	4.139^{**}		4.157^{**}	
R-square	0.206		0.234	

Note(s): $^{**}p < 0.01$. Estimate, unstandardized regression coefficients
[a]The number of days from the date of posting to the date of collecting
[b]Apparel, reference category

Table 6. Results of the OLS regression model

indicated no significant differences on like, comment, or follower counts between posts with highly product-centered comments and posts with comments irrelevant to the product.

Moreover, we examined the correlations among three performance metrics (i.e. like count, comment count and PCS). Follower count was also included into the correlation analysis. The results (see Table 7) indicate that like count is positively correlated with comment count ($r = 0.524, p < 0.01$), while there is no correlation between the PCS and like count or comment count. Moreover, the results show that follower count is positively correlated with comment count and like count ($r = 0.276, p < 0.01$; $r = 0.545, p < 0.01$) but not with the PCS.

5. Discussion

In contrast to our expectations, we find that the direct effects of vividness and coolness on product-centeredness are insignificant. From the perspective of the affective-cognitive model, cognitive and affective processes operate separately, while higher-order cognitive processing may strengthen or weaken the outcome of lower-order affective processing when processing resources are sufficient. For example, after considering social appropriateness (cognitive judgment), the action tendency triggered by negative affective stimuli may therefore be suppressed (Berkowitz, 1993).

Variable	(1)	(2)	(3)	(4)
(1) PCS	1.00			
(2) Comment count	0.020	1.00		
(3) Like count	−0.080	0.524^{**}	1.00	
(4) Follower count	−0.074	0.276^{**}	0.545^{**}	1.00

Note(s): $^{*}p < 0.05$; $^{**}p < 0.01$

Table 7. Results of the correlation analysis

Accordingly, no significant direct effects of vividness and coolness (i.e. affective stimuli) may result from the suppressing influence of authenticity, congruence, or other cognitive factors. Yet, this explanation remains to be rigorously examined in future studies. Identifying the conditions under which the suppression occurs is also needed. Despite this, our results indicate that coolness strengthens the effect of authenticity on product-centeredness. Thus, the role of affective stimuli cannot be neglected.

Different from coolness, the interaction of vividness with authenticity is not significant. A possible explanation may be the lack of imagining instructions in our research setting. Petrova and Cialdini (2005) found that when consumers are instructed to imagine that they have experienced the context in advertisements, high vividness enhances consumers' brand attitude and purchase intention. However, without imagining instructions, the effect of vividness does not exist. Hence, its relationship with post vividness needs to be further explored.

In line with prior research (Rutter *et al.*, 2021), the results of the supplementary analysis show that the number of followers is positively associated with the numbers of likes and comments. More importantly, according to the results, there is no correlation between the number of followers, likes, or comments and the PCS. Therefore, influencers' follower counts and volume-based metrics may not be good predictors of product-centeredness. This supports Gräve's (2019) view that the engagement rate may be insufficient to measure the effectiveness of influencer marketing.

Moreover, we find that some branded posts with high numbers of likes or comments have a relatively low PCS. Hence, content-based metrics should not be overlooked, although the engagement rate remains of importance in influencer marketing. We suggest that metrics for measuring comment content need to be specifically created.

6. Research contributions and managerial implications

This study contributes to social influencer marketing. Methodologically, it proposed a new instrument (i.e. the PCS) for measuring the product-centeredness in comment content by applying word embedding techniques in natural language processing. The PCS can be used in future research as a proxy variable to analyze comment content. The application of PCSs can reduce researchers' time and effort required for manual coding.

This research also extends our understanding of social media users' responses to influencers' branded posts. Prior research on performance metrics has focused primarily on measures such as like counts, comment counts and their determinants (Tafesse and Wood, 2021). This study instead identifies factors that drive comment content to be more product-centered. Moreover, our findings demonstrate the interplay among three performance metrics of influencer marketing, thus advancing our knowledge of building up a comprehensive metric system.

Practical implications for implementing influencer marketing programs can be derived from our findings regarding the antecedents of product-centeredness. First, branded posts that are highly authentic and cool are encouraged. For example, a product can be integrated into an influencer's life in a cool way. Second, marketers can develop a list of influencers whose profession or areas of interest match their product type and build long-term cooperative relationships with them.

Third, brands are advised to create and adopt the PCS as a performance metric and word-of-mouth management tool. Comment content provides firms with information they cannot gain from the numbers of likes and comments. Additionally, since comments on social media are read by other users, it is critical for marketers to detect consumers' opinions about their products. Aside from measuring post impact, the PCS enables firms to locate the voices of consumers, thereby allowing marketers to understand their consumers better and handle complaints speedily.

Furthermore, the proposed PCS has adequate validity and its calculation is easy for firms to follow and perform. We used pre-trained word embeddings available online and a straightforward method to obtain comment vectors. However, firms could apply more sophisticated techniques in natural language processing such as doc2vec (Le and Mikolov, 2014) if larger computational resources were available.

7. Limitations and future research directions

There are a few limitations in this study. First, this exploratory study centers on post characteristics and influencer–product congruence. Other possible contributing factors such as the traits of viewers also need to be considered. However, our data collection does not allow us to obtain the commenters' personal information. Future studies could explore how viewers' age, occupation and interests as well as behavioral variables influence product-centeredness using different methodologies. Second, this study focuses on product-centeredness. Future research could further compare the relative impact of product- and influencer-centered comments on consumers.

Third, the primary content generated by users varies by platform type (e.g. video- and photo-focused). Our analysis is based on Instagram posts, a major photo-sharing social media. Future research could consider different platform types such as YouTube on which users share videos. Finally, the posts that this study analyzed were written in Chinese. However, linguistic and cultural differences may affect the comment content on social media. Replicating this study in different cultural settings in the future may provide new insights.

Note

1. Significant correlations were also found between the scores from human raters and PCSs based on Word2Vec, a word embedding method (Mikolov *et al.*, 2013).

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Appendix

Product category	Product-category words
Beverage	Soda, coffee, juice, tea, liquor, milk and water
Food	Snack, bread, pasta, noodle, candy, dessert, supplements and nuts
Cosmetics	Makeup, lotion, cleanser, perfume and shampoo
Apparel and accessories	Clothing, shoes, jewelry, backpacks and watches
Consumer electronics	Laptops, appliances, speakers, cameras, chargers and earphones

Table A1.
Product-category words for sample posts

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