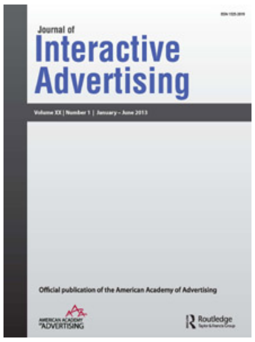

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Investigating Consumer Engagement with Influencer- vs. Brand-Promoted Ads: The Roles of Source and Disclosure

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Investigating Consumer Engagement with Influencer- vs. Brand-Promoted Ads:

The Roles of Source and Disclosure

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ABSTRACT

Brands' investments in influencer marketing have been escalating over the past few years. This study proposes and explicates how two similar and comparable sets of advertisements, namely influencer- vs. brand-promoted ads (i.e., influencer-generated ads and brands' reposting/featuring of influencer ads), can affect consumer engagement, consumer sentiment, and topics of comments differently. Results of text analysis show that influencer-promoted ads enjoy significantly higher engagement in terms of consumer liking and commenting than that of brand-promoted ads among apparel brands on Instagram. Consumers express a significantly higher percentage of negative sentiment and a lower percentage of positive sentiment in their comments on brand-promoted ads than on influencer-promoted ads. Consumers demonstrate cult-like appreciation for influencers' product sharing and show high involvement in the advertised products in influencer-promoted ads. Nonetheless, brand-promoted ads also positively affect consumers' interests in the online stores and/or the advertised products.

Keywords: influencer marketing, text analysis, consumer engagement, consumer sentiment, topic modeling

The growing popularity of online and social media, as well as their integration into people's daily lives in comparison to traditional media, provides marketers with the opportunity to transform their strategies to adapt to this new trend. However, given the fact that the use of ad blockers is still on the rise (O'Reilly 2017), advertisers face more challenges than before in reaching their target audience effectively. Among a multitude of innovative marketing strategies with which marketers have been experimenting, influencer marketing has emerged to be a cost-effective approach for brands to have more direct and organic contacts with potential consumers (Talavera 2015).

Influencers are key opinion leaders who have established likable personalities by regularly creating and disseminating content – usually online or on social media – and have accumulated a large number of followers (Lou and Yuan 2019; Swant 2016). Unlike celebrities or well-known public figures who have established their popularity via traditional mass media, influencers are usually viral content generators who have high visibility on social media and can wield influence over their followers (Garcia 2017). Influencer marketing thus refers to the type of marketing in which brands rely on social media's reach and invest in selected social media influencers to promote their products or services (Noyan 2017; Varsamis 2018).

With its unique advantages, influencer marketing has been proclaimed "the next big thing" (Agrawal 2016). Compared with advertising expenditure on traditional media or celebrity endorsements, influencer marketing content is relatively more cost-effective and easier to produce (Noyan 2017). Specifically, 94% of marketers who have implemented influencer marketing rated it as an effective strategy (Ahmad 2018). Although recent research has investigated issues relevant to the phenomenon of influencer marketing (e.g., De Veirman, Cauberghe, and Hudders 2017; Djafarova and Rushworth 2017; Evans et al. 2017; Johansen and

Guldvik 2017; Lou and Yuan 2019), to the best of our knowledge, none of them directly investigated whether and how influencer-promoted ads outperform other types of ads (e.g., brand-promoted ads). This study aims to fill this research gap.

Present-day brands can distribute branded content and advertisements not only through influencers but also via social media fan pages and/or brand accounts. This study thus compares the efficacy of two similar and comparable sets of marketing content, namely influencer-promoted branded posts and brands' reposting of influencers' branded posts. Theoretically, the findings of this study advance the current literature on influencer marketing via conducting a head-on comparison between the effectiveness of influencer-promoted ads and that of brand-promoted ads (i.e., brands' reposting of influencer ads) on social media. The findings of this study also offer lucid theoretical arguments on the relationships between the source/disseminator of advertisements, consumer engagement, and consumer sentiment in the context of influencer marketing. These findings undoubtedly yield theoretical and practical implications. Lastly, this study sheds light on the "black box" of consumer reactions via the summarization of the topics in consumer comments. The findings of this study lay the foundation for further theoretical building accounting for the mechanism through which influencers (vs. brands) affect consumers' engagement with advertisements and their subsequent consumption-related behaviors via social media.

LITERATURE REVIEW

Influencer Marketing and Social Media

There is a plethora of ways for brands to engage their target audience online, such as brand ads, paid ads, electronic word of mouth (eWOM), and so on. Over the past few years, eWOM has extended beyond friends' and family members' influence and evolved into a broader realm – influencer marketing (Talavera 2015). A social media influencer (thereafter "influencer") has been defined as "a content generator; one who has a status of expertise in a specific area, who has cultivated a sizable number of captive followers – those are of marketing value to brands – by regularly producing valuable content via social media" (Lou and Yuan, 2019, p. 59). Influencers' appeal to the market has been well-acknowledged. A recent report from Twitter showed that people trust social media influencers almost as much as they trust their friends (Swant 2016). Nearly 40% of Twitter users have made a purchase at some point because of an influencer's recommendation (Karp 2016), and 70% of teenage YouTube users reported that they consider YouTube influencers "more like one of us" and relate to them more than they do to traditional celebrities (O'Neil-Hart and Blumenstein 2016).

Among a variety of social media platforms that boast influencers, this study selected Instagram, a highly relevant platform, to examine the influencer phenomenon. As a mobile-based social networking app for photo and video sharing, Instagram exhibits a higher engagement potential for brands to engage consumers than other platforms such as Facebook, Twitter, or Pinterest (TrackMaven 2016). It also provides unique affordance in which influencers can tag brands and brands can set up shoppable product tags in photos and videos (Instagram 2019). A recent study surveying 300 influencers showed that 99.3% of these influencers considered Instagram their top destination to connect with brands and community (Morrison 2017).

This study selected apparel brands to compare influencer-promoted ads' effectiveness with that of brand-promoted ads. Given that 98% of fashion brands have joined Instagram as of March 2016 (Statista 2017), apparel brands enjoy both phenomenal follower growth and high content engagement (TrackMaven 2016, p. 5). Fashion-related or apparel-related influencers are making an impressive amount of money out of partnering with brands (Thompson 2016). Since apparel brands produce popular products that are indispensable to the majority of consumers' daily lives, examining apparel brands' influencer marketing on Instagram could largely reflect average consumers' engagement behaviors and reactions.

Source and Persuasion Knowledge

According to McGuire's communication-persuasion matrix (McGuire 2001), a multitude of input components in persuasive communication, including source, message, channel, receiver, and destination, can affect persuasion effects. A source is defined as a message sender or creator (Ohanian 1990). This study focuses on "source" as an ad distributor – either a brand or an influencer on social media – who is expected to play a role in consumer behavior.

Although there is a lack of empirical evidence on the role of influencer (vs. brand) in consumer reactions, given that influencers (or "micro-celebrities") are content creators with "celebrity" status on social media, we draw on the literature of celebrity endorsement. For instance, celebrities are generally perceived to be more trustworthy than brands (Freiden 1984; Ohanian 1991), and celebrity endorsements have been found to be effective in eliciting favorable responses (e.g., Amos, Holmes, and Strutton 2008) and revenue increase (Elberse and Verleun 2012). More importantly, the source of advertisements on social media (e.g., celebrities vs. brands) has been found to affect consumers' persuasion knowledge (e.g., Boerman, Willemsen, and Van Der Aa 2017; Wood and Burkhalter 2014).

Persuasion Knowledge Model (PKM) (Friestad and Wright 1994) describes the mechanism through which consumers develop knowledge about persuasive intents and tactics and understand the reasons why marketers or ads try to influence them in a certain context. Accordingly, consumers can use the knowledge to deal with persuasive attempts and refine their attitudes or behavior intentions toward products and brands. Consumers' ability to identify messages with persuasive intents precedes their potential use of any coping skills (Rozendaal et al. 2011). Persuasion knowledge comprises a cognitive dimension and an attitudinal dimension (Hudders et al. 2017; Rozendaal et al. 2011). Conceptual persuasion knowledge (CPK) entails recognizing a persuasive message as an ad and identifying marketing tactics employed during the process, whereas attitudinal persuasion knowledge (APK) depicts the attitudinal mechanism – critical attitudes such as skepticism or dislike – that can be activated when individuals cope with persuasive attempts (Rozendaal et al. 2011).

Since influencers are akin to celebrities (Lou and Yuan 2019), we draw on prior literature that examined the roles of brands and celebrities in consumers' persuasion knowledge. When comparing brand-promoted ads with celebrity endorsements, Boerman and colleagues (2017) argued that, since brands are non-human entities and celebrities are human agents, consumers, due to the correspondence bias, are more likely to attribute celebrity endorsements to honest positive opinions rather than financial compensation (Gilbert and Malone 1995). Also, brands' postings on social media generally have explicit intentions to persuade consumers, whereas celebrities' motivations for posting an ad cannot always be readily identified (Wood and Burkhalter 2014). Indeed, consumers can always readily recognize a brand-promoted ad on social media as advertising and adding a disclosure will not further improve their CPK, whereas consumers indicated significantly lower CPK for a celebrity-promoted ad without a disclosure than the same ad with a disclosure (Boerman, Willemsen, and Van Der Aa 2017). When it comes to influencer advertising, ads disseminated by influencers tend to correspond with influencers' online persona and lifestyle, and thus look more like organic user-generated posts when compared with brand-promoted ads (Newberry 2018). Collectively, we argue that followers are less likely to recognize an influencer post as advertising and are more likely to recognize a brand post as advertising.

Upon viewing influencer- and brand-promoted ads, followers' activated persuasion knowledge will influence their subsequent engagement with the ads (Boerman et al. 2017; Hwang and Zhang 2018). In this study, we investigated three aspects of followers' engagement – engagement in terms of liking and commenting, sentiment, and topics of comments – and proposed a conceptual model that effectively summarizes this study (see Figure 1).

PLACE FIGURE 1 HERE

Consumer Engagement, Sentiment, and Topics of Comments

Consumer engagement. The concept of consumer engagement has its roots in the realm of relationship marketing (Ashley et al. 2011; Vivek, Beatty, and Morgan 2012). Vivek et al. (2012) defined customer/consumer engagement as "the intensity of an individual's participation in and connection with an organization's offerings or organization activities, which either the customer or the organization initiates" (p. 127). Such a conceptualization of consumer engagement offers a broader approach to understanding consumers' interactions with brands, products, or other consumers, which go beyond actual purchases or exchange intentions.

In the context of social media and online media, studies have focused on the behavioral dimension of consumer engagement (e.g., liking and commenting) (e.g., Barger, Peltier, and Schultz 2016; Gummerus et al. 2012; Verhagen et al. 2015), and further explicated the mechanism through which engagement influences consumer behaviors (e.g., eWOM and purchase intentions) (e.g., Alhabash et al. 2015; Erkan 2015; Vivek et al. 2012). Specifically, consumer engagement on social media has been measured by engagement metrics that gauge a set of behavioral responses, such as viewing, liking, sharing, and commenting (e.g., Barger et al. 2016; Coelho, Oliveira, and Almeida 2016; Erkan 2015; Gummerus et al. 2012). Accordingly, this study used engagement metrics (i.e., number of likes and comments) to operationalize and to measure consumers' engagement with social media ads. As consumers are more likely to recognize a brand post (vs. an influencer/celebrity post) as advertising (Boerman et al. 2017; Wood and Burkhalter 2014), consumers' activated persuasion knowledge – recognizing advertising – negatively influenced their engagement intentions towards the ads/posts (Boerman et al. 2017; Hwang and Zhang 2018). Therefore, we propose that:

H1: Consumers are more likely to engage with influencer-promoted ads than brand-promoted ads.

Since brand-promoted ads will be readily recognized as advertising, the inclusion of sponsorship disclosure may not be necessary for brand-promoted ads (Boerman et al. 2017). However, the presence of sponsorship disclosure (vs. no disclosure) has been found to increase consumers' CPK for celebrity- or influencer-promoted ads (Boerman et al. 2017; Evans et al. 2017). In particular, clear disclosure (e.g., #PaidAd) produced more CPK than ambiguous disclosure (e.g., #SP), and the presence of disclosure, regardless of language variation, led to higher CPK than no disclosure (Evans et al. 2017). Moreover, consumers' CPK can influence consumers' engagement with the ads (Boerman et al. 2017; Hwang and Zhang 2018). Taken together, we argue that:

H2: Consumers are least likely to engage with influencer-promoted ads with clear disclosures, followed by ads with ambiguous disclosures and those without disclosures.

Besides gauging consumers' behavioral engagement or interactions with ads, examining consumers' sentiment embodied in the conversations is also crucial to brands and firms (Homburg, Ehm, and Artz 2015).

Consumer sentiment. Consumer sentiment, which originates from the realm of behavioral economics, is argued to influence human beings' economic behavior (Kellstedt, Linn, and Hannah 2015). Consumer sentiment and consumer attitudes have been used interchangeably to refer to consumers' valenced, aggregate, and subjective evaluation of a phenomenon (e.g., marketing in a country) or an object (e.g., product and economy) (e.g., Gaski and Etzel 1986; Shahriar Ferdous and Towfique 2008). Consumer sentiment can be gauged by survey instruments (e.g., Gaski and Etzel 1986) and automatic sentiment analysis of texts (e.g., Mostafa 2013; Pang and Lee 2008). Herein, this study adopted automatic sentiment analysis, which involves computational techniques and natural language processing, to classify a large body of textual content (e.g., online comments and social media posts) as positive, neutral, or negative (Liu 2012; Mostafa 2013).

User-generated content (e.g., comments and reviews) and social media posts have become valuable sources for sentiment analysis to generate useful results for brand management (Mostafa 2013), product evaluation tracking (Villarroel Ordenes et al. 2017), and monitoring of consumer dissatisfaction (Qiu et al. 2010). Relevant to this study, since consumers are less likely to recognize influencer-promoted content (vs. brand-promoted ads) as advertising, recognizing ads – namely CPK – precedes and leads to the activation of attitudinal persuasion knowledge

(APK) towards the ads (i.e., critical attitudes and dislike) (Boerman et al. 2012, 2017). We posit that,

H3: Consumers will demonstrate more positive sentiment and less negative sentiment in their comments on influencer-promoted ads than on brand-promoted ads.

Additionally, consumers will be most likely to recognize influencer-promoted ads with clear disclosures as advertising than those with ambiguous disclosures, followed by those without disclosures (e.g., Evans et al. 2017). Activated CPK in turn, is expected to lead to the activation of APK (i.e., critical attitudes and dislike). Thus, we argue that:

H4: Consumers will demonstrate the least positive sentiment and the most negative sentiment in their comments on influencer-promoted ads with clear disclosures, followed by ads with ambiguous disclosures and those without disclosures.

Topics of comments. A multitude of research has so far examined the characteristics of online reviews/comments (e.g., Mudambi and Schuff 2010; Willemsen et al. 2011) and their roles in consumer behavior (e.g., Park and Lee 2009; Park, Lee, and Han 2007). These studies often investigated the relationships between review traits, perceived review usefulness, and purchase intentions. However, these studies rarely focused on analyzing the reviews/comments. Investigating consumers' topics of comments/reviews is crucial to brand management (Farjami 2019). Since online comments reflect up-to-date consumers' interests and focuses, recent research advocates using topic modeling to extract useful trends or topics from online reviews/texts, which can facilitate many applications in brand management and/or advertising practices (e.g., Calheiros, Moro, and Rita 2017; Korfiatis et al. 2019; Liu, Burns, and Hou 2017). For instance, Calheiros and colleagues (2017) used topic modeling to classify online reviews of a hotel into nine major topics (e.g., food, location, romance, and hospitality). They appraised the trend underneath each topic and used this information to improve hotel management.

This study intends to determine the topics underlying consumers' comments on influencer- and brand-promoted ads, how their topic patterns may differ from each other, and how the topics for influencer ads with clear disclosures, ads with ambiguous disclosures, and those without disclosures differ from each other. Therefore, the following questions are advanced:

RQ1: What are the topics of consumer comments on influencer- and brand-promoted ads, and how they differ from each other?

RQ2: What are the topics of consumer comments on influencer ads with clear disclosures, ads with ambiguous disclosures, and those without disclosures, and how they differ from each other?

METHOD

Data Collection and Extraction

The current study used the latest list of top 50 apparel companies in the U.S. (Apparel Magazine 2016) and looked into their influencer marketing campaigns on Instagram. For each of the 50 companies, their flagship brands (one to two) were selected to represent the company. Since this study compares campaigns among apparel brands that cater primarily to adolescents and adults, brands that target kids, babies, and pregnant women, or those featuring corporate uniforms, were excluded. A total of 44 brands were identified, three of which do not have Instagram accounts, resulting in a total of 41 brands for data extraction.

To avoid holiday season advertising or campaigns in the fall, we chose the spring season of 2017 (March 1 to May 31) as the time period for data extraction. The unit of analysis is the Instagram post that can be identified as an influencer campaign ad. First, two researchers examined each of the 41 brands' Instagram accounts and tried to locate all influencer marketing ads between March 1 and May 31, 2017. Brands or influencers usually covertly or overtly mention their sponsor-partner relationships in the posts. Since brands tend to repost influencers' pictures or branded content on their Instagram accounts to further promote the advertised products or services, the researchers first located ads featuring both an influencer and product(s) from a brand's Instagram page. Second, the researchers went through the featured influencers' Instagram pages to pinpoint the exact ad that was originally promoted on the influencers' accounts. If the identical picture could not be identified from the influencers' accounts, similar ads in which the influencers wore the same attire and promoted the same products (as shown in brands' posts) were selected. The chosen brand-promoted and influencer-promoted ads had high temporal proximity in posting time. Brand-promoted ads featuring in-house models, brand-fan interactions, or renowned celebrities were excluded.

The two researchers independently identified a list of influencer-promoted ads and a list of brand-promoted ads (percentage of agreement: 96.7%) (see Appendices). The acquired lists were compared against each other, discussed, and revised to reach a final consensus. A total of 145 dyads – brand- and influencer-promoted ads – were found, including 27 brands and 138 influencers. We used R software to create an authentication process and retrieved data via the Instagram Application Programming Interface (API) (R-bloggers 2014). For each Instagram post, the researchers extracted posting date, the number of likes, the number of comments, comments, sponsorship disclosures for influencer-promoted ads (if applicable), and the Instagram account's total number of followers. For influencer-promoted ads (n = 145), we classified the ads into three categories – ads without disclosure (n = 88), ads with ambiguous disclosure (n = 11, "#partner",

"#sp"), and ads with clear disclosure (n = 32, "#ad" or "#sponsored"). Fourteen post URLs were disabled after initial data extraction and were thus not considered.

Data Analysis

Engagement Metrics. In alignment with prior research that measured consumers' engagement with Instagram brand posts via examining their liking and commenting metrics (Coelho et al. 2016; Erkan 2015), we operationalized behavioral consumer engagement on Instagram by measuring the engagement metrics of liking and commenting. Consumer engagement metrics are defined as "the average number of interactions per post per 1,000 followers" (TrackMaven 2016, p. 8). For each ad, the average number of likes/comments per ad per 1,000 followers was calculated to reflect its liking/commenting engagement metrics. The 145 posts' engagement metrics were then averaged to show the mean engagement metrics.

Sentiment analysis. To categorize followers' sentiment in their comments on influencer- and brand-promoted ads, we built sentiment analysis models using support vector machine (SVM) (Cortes and Vapnik 1995), a supervised machine learning algorithm that has been proven effective in sentiment classification (e.g., Chikersal, Poria, and Cambria 2015; Kiritchenko, Zhu, and Mohammad 2014). Constructing an SVM model entails learning a decision boundary from manually annotated data. We used Mohammad and Bravo-Marquez's (2017) WEKA package to generate word and character n-grams, negations, part-of-speech tags, brown clusters, lexical features, sentiment strengths, and word embeddings as features for learning the decision boundary. This package was originally introduced for sentiment analysis of tweets. Since tweets have many commonalities with comments on Instagram, the same set of features is well-suited to the classification of Instagram comments. We combined two datasets to train the SVM models. The first dataset (Mohammad, Sobhani, and Kiritchenko 2017) contains 1,524 positive tweets, 3,034 negative tweets, and 312 neutral tweets. Since the class distribution of this dataset is skewed and it is often more challenging to build a good classification model with imbalanced classes, 865 positive tweets and 708 neutral tweets from another dataset (Mohammad et al. 2018) were added to balance the classes. Two SVM models were created, one for separating negative comments from non-negative comments and one for separating positive comments from non-positive comments. The two SVM models were then deployed to classify the 6,412 comments on influencer-promoted ads and the 7,130 comments on brand-promoted ads.

Topic Modeling. We adopted a topic modeling approach to test RQ1 and RQ2. Topic modeling uses statistical models to discover latent topical patterns from texts. It provides a convenient means to summarize information (Arora et al. 2013) and to detect thematic topics in social media and online textual content (Anoop and Asharaf 2017). We used Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003) – one of the most popular methods for topic modeling – in R software (*topicmodels* package). LDA assumes that every document contains a set of topics and that each topic is associated with a small number of topic keywords. Given a collection of texts and the number of topics (i.e., K*)* that specifies how many topics to be discovered, LDA returns a list of keyword clusters that best represent the topics in the collection.

Preprocessing of data is essential to topic modeling. We followed the preprocessing steps described by Maier et al. (2018). Most of the steps, including case folding, removal of punctuation and non-alphanumeric symbols, stop words removal, and lemmatization, are standard preprocessing steps in many text mining tasks. In addition to these common steps, Maier et al. (2018) have proposed that using relative pruning to strip extremely rare and extremely frequent terms from the data would stabilize the performance of LDA topic models. They suggested that terms that occur in less than 0.5% of documents or more than 99% of documents should be pruned. These thresholds, however, would not work well for our data. For example, using the influencers' data which consist of 6,412 comments, the upper threshold (99% or 6,348 comments) would remove nothing because it is too high, while the lower threshold (0.5% or 32 comments) would remove too many useful terms because most of the terms in the data occur in less than 32 comments. Therefore, relevant to the nature of our data sets, we adopted a frequency count of two as the lower threshold and a frequency of 5% as the upper threshold.

Another critical factor in topic modeling is the choice of K, i.e., the number of topics to be extracted. Maier et al. (2018) posited that "interpretability should be the prime criterion in selecting candidate models" (p. 18). "While LDA is relatively robust to changes in the number of topics (Stevens et al. 2012), many topics learned this way can still be either duplicates of each other or irrelevant for classification or further analysis. Human judgment is needed to distinguish between them" (Puschmann and Scheffler 2016, p. 4). We first adopted the intrinsic coherence measure, a quantitative measure that gauges topic coherence (Maier et al. 2018; Mimno et al. 2011), for initial model selection. After calculating the intrinsic coherence for K = 3, 4, 5, …, 20, the researchers reached a consensus that the topics extracted using the 5-topic model were most clear-cut and interpretable for the comments on each set of the influencer- or brand-promoted ads, respectively. For the three subsets of comments on influencer-promoted ads without disclosure, ads with ambiguous disclosures, and ads with clear disclosures, the 3-topic model was most recommended and was thus adopted for each subset of the comments.

With K = 5 or K = 3, LDA returned five or three keyword clusters, for which human interpretation was required to determine the topic represented by each cluster (e.g., Calheiros, Moro, and Rita 2017; Moro, Cortez, and Rita 2015; Rohani, Shayaa, and Babanejaddehaki 2016).

We ordered the keywords by their β values – which correspond to the significance of the keywords based on log-likelihood – to facilitate interpretation of the topics.

RESULTS

Hypothesis 1 posits that consumers are more likely to engage with influencer-promoted ads than brand-promoted ads. Results of the independent samples *t*-test indicated that an influencer-promoted ad, on average, enjoyed significantly higher engagement in terms of consumer liking than that of a brand-promoted ad ($M_{influencer} = 54.65$, $SD = 56.99$; $M_{brand} = 8.77$, $SD = 5.62$, $t\ (288) = 9.648$, $p < .001$): 55 out of 1000 followers liked an influencer-promoted ad and an average of nine out of 1000 liked a brand-promoted ad. Similarly, an influencer-promoted ad enjoyed significantly higher engagement in terms of consumer commenting than that of a brand-promoted ad ($M_{influencer} = 2.71$, $SD = 4.01$; $M_{brand} = 0.06$, $SD = 0.09$, $t\ (288) = -7.976$, $p < .001$): an average of three out of 1000 followers commented on an influencer-promoted ad, whereas none of them commented on a brand-promoted ad. Therefore, H1 was supported.

Hypothesis 2 postulates that consumers are least likely to engage with influencer-promoted ads with clear disclosures, followed by ads with ambiguous disclosures and those without disclosures. One-way analysis of variance (ANOVA) tests were conducted to compare consumer engagement across the three types of influencer ads. Results showed no significant difference in terms of consumer liking ($M_{no\ disclosure} = 55.25$, $SD = 57.18$; $M_{ambiguous} = 55.49$, $SD = 68.79$; $M_{clear\ disclosure} = 48.91$, $SD = 53.20$, $F\ (2, 130) = .15$, $p = .86$) or commenting ($M_{no\ disclosure} = 2.99$, $SD = 4.36$; $M_{ambiguous} = .88$, $SD = 1.04$; $M_{clear\ disclosure} = 2.71$, $SD = 4.15$, $F\ (2, 130) = 1.26$, $p = .29$) across the three types. H2 was not supported.

Hypothesis 3 proposes that consumers will demonstrate more positive sentiment and less negative sentiment in their comments on influencer-promoted ads than on brand-promoted ads.

Results of sentiment analysis revealed that comments on influencer-promoted ads had a higher percentage of positive sentiment (76.36%) than those on brand-promoted ads (54.40%). The proportion of positive vs. non-positive sentiments in the two sets of comments differed significantly from each other (X^2 (1, n = 13,542) = 713.28, $p < .05$). Also, comments on influencer-promoted ads had a lower percentage of negative sentiment (0.09%) than those on brand-promoted ads (0.43%). The proportion of negative vs. non-negative sentiments in the two sets of comments differed significantly from each other (X^2 (1, n = 13,542) = 14.42, *df = 1*, $p < .05$). H3 was thus supported.

Hypothesis 4 posits that consumers will demonstrate the least positive sentiment and the most negative sentiment in their comments on influencer-promoted ads with clear disclosures, followed by ads with ambiguous disclosures and those without disclosures. Results showed that both influencer-promoted ads without disclosures and those with clear disclosures received greater proportion of positive sentiment than those with ambiguous disclosures (no disclosure vs. ambiguous disclosure: X^2 (1, n = 4,371) = 4.70, $p < .05$; clear vs. ambiguous disclosure: X^2 (1, n = 1,986) = 4.50 $p < .05$) (see descriptives in Table 1). However, the proportion of positive sentiment in the comments on those without disclosures and those with clear disclosures did not significantly differ from each other (X^2 (1, n = 5,529) = 0.03, $p > .05$). Also, the proportion of negative sentiment in the comments on the three types of influencer-promoted ads did not significantly differ from each other (X^2 (1, n = 5,943) = 0, $p > .05$). H4 was not supported.

PLACE TABLE 1 HERE

RQ1 asked about the topics of consumer comments on influencer- and brand-promoted ads and how they differ from each other. Amongst the comments on influencer-promoted ads, the most frequently mentioned five topics were interpreted and labeled “compliment on advertised product," "appreciation for influencers' sharing," "compliment on influencers' style," "compliment on product features," and "purchase interest" (see Table 2). With regard to comments on brand-promoted ads, the most frequently mentioned five topics were about "compliment on influencers' style," "interest in online store," "compliment on the advertised product," "purchase interest," and "brand & brand-related social cause mentioning." For each topic, we identified the top five keywords, exemplary comments, and the percentage of comments containing the topic. For example, among all the comments on influencer-promoted ads, 70.06% were about topic 1 – "compliment on advertised product," as exemplified by comments like "Such a gorgeous jumpsuit" and "Oh this lace top is amazing."

PLACE TABLE 2 HERE

RQ2 focuses on the topics of comments on influencer ads with disclosures and those without clear or ambiguous disclosures and how they differ from each other. The topics extracted from the three types of influencer ads largely echoed what has been found in the topics of influencer ads as a whole (see Table 3). The only exception is that for influencer ads with clear disclosures, "life inspirations" emerged to be the top topic among the comments, referring to followers' general inspirational thoughts and positive reactions upon exposure to influencer ads.

PLACE TABLE 3 HERE

DISCUSSION

As influencer marketing has been gaining increasing traction and is yet to evolve, the findings of this study present informative guidance to brands and advertisers. The results show that influencer-promoted ads indeed spurred higher engagement and gleaned more positive sentiment from their followers when compared with that of the identical ads being re-disseminated by brands. Influencer-promoted ads, in general, garnered glowing comments and appreciation from their followers. Brands-promoted ads, on the other hand, received slightly less applause from their followers but increased the followers' interest in the advertised products. The types of disclosure (i.e., no disclosure, ambiguous, or clear disclosure) in influencer-promoted ads did not influence consumers' engagement activities. However, consumers expressed slightly less positive sentiment in their comments on influencer ads with ambiguous disclosures than on ads without disclosures or ads with clear disclosures.

In agreement with industry insights that applaud the desirable traits of influencer marketing (e.g., Agrawal 2016; Ward 2017), the findings of this study suggest that influencer-promoted ads elicit more engagement from followers when compared with brand-promoted ads. We argue that such finding can be explained by the discovery of the relationship between ad source and persuasion knowledge (e.g., Boerman et al. 2017; Wood and Burkhalter 2014): Brand-promoted ads (vs. influencer-promoted ads) are more readily recognized as advertising and can activate consumers' persuasion knowledge, which in turn, may negatively affect consumers' engagement with the ads. However, we do acknowledge that this study adopted a text analysis approach and did not measure persuasion knowledge.

Secondly, brand-promoted ads elicited slightly more negative sentiment and less positive sentiment than influencer-promoted ads. Drawing on the arguments on the link between ad source and persuasion knowledge (e.g., Boerman et al. 2017; Wood and Burkhalter 2014), presumably, consumers are more likely to recognize brand posts (vs. influencer posts) as advertising and thus are more likely to activate their attitudinal persuasion knowledge – critical attitudes and dislike expressed in the form of negative sentiments – which can contribute to less positive sentiments in their comments. Interestingly, followers' engagement activities (i.e., liking and commenting) towards the three types of influencer-promoted ads – ads without disclosures, ads with ambiguous disclosures, and ads with clear disclosures – did not differ. However, followers expressed less positive sentiment towards influencer-promoted ads with ambiguous disclosures than those either without disclosures or with clear disclosures. This finding largely echoes the results of a recent study (Dhanesh and Duthler 2019). Dhanesh and Duthler (2019) revealed that followers' recognition of influencer-promoted posts as advertising did not affect the influencer-follower relationship. Instead, influencers' sponsorship disclosures actually facilitated followers to perceive the influencers to be honest and transparent, which in turn, boosted followers' trust and satisfaction with the relationship. Our findings suggest that followers treat influencer-promoted ads without disclosures and those with clear disclosures in a similarly favorable fashion. However, they may find those with ambiguous disclosures (i.e., #partner) dubious and thus express less positive sentiment.

Lastly, with regard to the topic modeling results, comments on influencer- and brand-promoted ads share some common themes. For example, they both have topics that highlight consumers' "compliment on advertised product," "compliment on influencers' style," and "purchase interest." Since influencer marketing ads on Instagram predominantly feature influencers who are displaying a certain apparel product such as a top or a dress, it is not surprising to see a large number of compliments on the advertised products and the influencers' outfit style. Moreover, consumers demonstrated purchase interests in both sets of comments, as they frequently use verbs such as "need," "want," or "buy" in the comments.

It is noteworthy that the comments on the two types of ads also exhibit varied emphases. For instance, comments on influencer-promoted ads explicitly expressed "appreciation for influencers' sharing" and "compliment on product features." Such findings support the prediction of previous literature on the role of ad source in consumer reactions (e.g., Djafarova and Rushworth 2017; Gilbert and Malone 1995): Consumers tend to perceive influencer-promoted ads more as “altruistic” sharing, rather than the outcomes of financial compensation, and they appreciate influencer sharing and are more involved in the advertised products. Meanwhile, consumers on brand-promoted ads demonstrated topics such as “interest in online store” and “brand & brand-related social cause mentioning.” Previous research noted the effect of limited exposure to online banner ads on boosting brand awareness and ad awareness (Briggs and Hollis 1997); this current finding adds to prior literature and suggests that brand-promoted ads can positively affect consumers’ interests in online store or products.

Additionally, consumers’ topics in comments across the three types of influencer ads (without disclosure, with ambiguous, or clear disclosure) largely reflect the original five topics for influencer-promoted ads as a whole. Interestingly, consumers expressed inspirational thoughts upon exposure to influencer-promoted ads with clear disclosures. This again echoes what Dhanesh and Duthler (2019) argued: disclosure signals that influencers are transparent and genuine in building relationship with their followers, which in turn, spurs consumers’ positive reactions to influencers’ sharing.

Theoretical and Practical Implications

Theoretically, this study explicated the relationships between advertisement source, consumer engagement, consumer sentiment, and consumer topics in the context of influencer marketing. The findings of this study advance the current literature on the roles of influencers and brands in advertising performance. Specifically, this study proposed a conceptual model arguing how influencer- and brand-promoted ads influence consumer engagement differently, with engagement reflected in consumers’ behavioral engagement (i.e., liking and commenting) with the ads, consumer sentiment in their comments, and consumer topics in the comments.

During this process, the presence of sponsorship disclosures is expected to influence the effect of influencer-promoted ads. The findings of this study expand the existing literature on consumers' online engagement by considering consumer sentiment and topics in their comments. Specifically, the summarization of the topic themes in consumers' comments uncovered the "black box" of consumer reactions when they view ads disseminated either by "someone like me" or by brands. Such a nuanced understanding of the textual corpora pointed to several distinct constructs that relate to consumer reactions and behavior, which laid a foundation for a more comprehensive theoretical framework in the future.

Recent research on native advertising suggests that providing detailed disclosures can produce a positive effect on consumers' perception of sponsorship transparency and their subsequent credibility perception of the native ads, advertisers and news media (Krouwer, Poels, and Paulussen 2019). Campbell and Evans (2018) also indicate that higher sponsorship transparency can mitigate or even reverse the negative indirect impact of ad recognition. Practically, brands are advised to emphasize on disclosure transparency when promoting influencer-generated content, which may contribute to positive consumer perceptions. When assessing influencers' market value, besides assessing an influencer's potential reach (i.e., number of followers), brands should take into consideration the "stickiness" of the followers, namely, the behavioral engagement that an influencer post typically gets and the strength of the influencer-follower relationship. Additionally, brands should monitor consumers' focuses by tracking consumers' comments and sentiment, and accordingly coordinate their online or offline practices (e.g., online store, product offering, etc.). Besides abiding by the Federal Trade Commission (FTC)'s requirements by providing clear disclosures in sponsored posts (FTC 2017), influencers should also try to provide more detailed disclosures to boost sponsorship transparency, which may positively influence followers' credibility perception of the sponsored posts and the influencers, thus mitigating the negative impact of ad recognition.

Limitations and Future Directions

This study also bears some limitations. First, since we adopted a big data approach, we did not measure CPK in this study. Future research may adopt an experiment design in which they can manipulate the source of social media advertisements and disclosure types to test the role of CPK in consumer behavioral engagement, sentiment, and topics in their comments. Second, given the fact that influencers and brands voluntarily opt to disclose sponsorships in their posts on Instagram, even though the two researchers have reached a significant level of consensus on data extraction, there is still a slim chance that we may not have the exhaustive list of all influencer marketing campaigns during the selected period of time. Future researchers may want to replicate the current study by using a different time frame to see if they can reach a similar conclusion. Moreover, this study focused on top apparel brands, and future researchers may want to validate the current findings by investigating brands from other product categories. Lastly, since brands tend to repost influencer-promoted posts after influencers' initial posting, consumers who have followed both influencers and brands may only interact with the first post that they see. The effect of posts' originality should be accounted for in future research.

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TABLE 1

Sentiment Classification of Comments on Three Types of Influencer-promoted Ads

Types of influencer ads	**Total number of comments**	**Sentiment classification (% of positive vs. % of non-positive)**	**Sentiment classification (% of negative vs. % of non-negative)**
No disclosure (n = 88)	3957	75.51% vs. 24. 49%	0.08% vs. 99.92%
Ambiguous disclosure (n = 11)	414	61.35% vs. 38.65%	0.24% vs. 99.76%
Clear disclosure (n = 32)	1572	74.79% vs. 25.21%	0.13% vs. 99.87%

TABLE 2

Topics Extracted from Comments on Influencer- vs. Brand-promoted Ads

Topic	**% of comments containing the topic**	**Comment Examples**	**Top keywords and their β values**
Topics for Comments on Influencer-promoted Ads			
Compliment on advertised product	70.06%	• Such a gorgeous jumpsuit • Oh this lace top is amazing	top (-2.53) gorgeous (-2.57) thank (-2.81) great (-3.02) amazing (-3.18)
Appreciation for influencers' sharing	64.50%	• Great shot babe xo • Oh what a cool pic!	thanks (-2.75) babe (-3.16) nice (-3.17) good (-3.36) cool (-3.60)
Compliment on influencers' style	41.17%	• Your summer style is as trendy and pretty as your winter style • Loving that style	pretty (-2.34) outfit (-3.19) style (-3.31) loving (-4.00) ootd (-4.26)
Compliment on product features	29.55%	• Those shoes!! And the print in that skirt is beautiful • LOVING those details! That color is stunning.	dress (-2.19) beautiful (-2.31) wow (-3.22) color (-3.55) shoe (-3.65)
Purchase interest	20.46%	• Looks great! I want to get one but can't find it on the website!!! • I love it!!! Is it stretchy? I want to get it, just wanting to make sure it'll fit my preggo belly	get (-3.46) just (-3.53) much (-3.54) one (-3.71) see (-3.75)
Topics for Comments on Brand-promoted Ads			
Compliment on influencers' style	60.31%	• I would 100% wear this entire outfit • Styled so perfectly! :)	dress (-3.46) style (-3.55) outfit (-3.63) thank (-3.68) shirt (-3.69)
Interest in online store	55.01%	• Is this shirt available? Didn't see it online. • I don't see this listed in the store?	look (-2.54) see (-3.45) store (-3.53) thanks (-3.61) check (-3.79)
Compliment on advertised	38.32%	• That dress is beautiful • Please bring back the top!!!	cute (-2.57) nice (-3.12)

product		Soooo cute!!!	beautiful (-3.25) omg (-3.26) cool (-3.57)
Purchase interest	22.90%	• Want these ! Need these! Can't wait to get my hands on them! • I like both top and jeans. Wish I could go and get one	need (-2.87) like (-2.93) get (-2.94) want (-3.49) think (-3.59)
Brand & brand-related social cause mentioning	20.13%	• Thanks @lululemon for your support of @irongirlnadia • @charitymiles and @lululemon are like a match made in heaven	lululemon (-3.10) great (-3.20) charitymiles (-3.27) awesome (-3.44) please (-3.59)

Note. LDA topic modeling can assign multiple topics to each comment, therefore, the percentage for all topics would not add up to 100% (it should be > 100%). The distribution only counted the top three most prominent topics of each comment. The top five topic keywords for each topic are presented with the β values that correspond to the significance of the keywords based on log-likelihood. The larger the β value (minus value), the stronger the relation between a keyword and the topic.

TABLE 3

Topics Extracted from Comments on Three Types of Influencer-promoted Ads

Topic	**% of comments containing the topic**	**Comment Examples**	**Top keywords and their β values**
Topics for Comments on Influencer-promoted Ads without Disclosures			
Compliment on advertised product	65.66%	• That top is so pretty! • Nice dress	top (-2.68) pretty (-2.84) dress (-2.85) amazing (-3.04) nice (-3.48)
Appreciation for influencers' sharing	55.04%	• Wow awesome shot. It's so beautiful! • Wow gorgeous shot!	beautiful (-2.78) gorgeous (-3.11) thanks (-3.23) shot (-3.39) wow (-3.50)
Compliment on influencers' style	28.96%	• Great outfit! I really love the top! • Great style	great (-3.12) thank (-3.32) outfit (-3.53) omg (-3.69) style (-3.79)
Topics for Comments on Influencer-promoted Ads with Ambiguous Disclosures			
Compliment on advertised product	57.97%	• Gorgeous top! Loving this outfit • Love the mix of stripes	cute (-2.22) outfit (-2.45) gorgeous (-2.51) yellow (-2.91) stripe (-2.91)
Appreciation for influencers' sharing	49.28%	• Such a fabulous shot babe • Awesome shot!!	beautiful (-2.49) babe (-2.76) shot (-2.92) one (-3.12) jacket (-3.12)
Purchase interest	29.47%	• Love your bag! Where is from? • I definitely need this top!	pretty (-2.61) great (-2.61) happy (-2.68) bag (-2.76) get (-2.84)
Topics for Comments on Influencer-promoted Ads with Clear Disclosures			
Life inspirations	58.69%	• I hope to learn to live in (and ENJOY) the moment! • I'd hope to learn how to continue to have fun and never take things to seriously. Time is precious.	thing (-3.14) learn (-3.14) hope (-3.25) moment (-3.61) thanks (-3.65)

Compliment on influencers' style	44.11%	• Omg! This outfit is gorgeous! Love it on you! • So gorgeous girl	gorgeous (-3.01) thank (-3.37) outfit (-3.45) girl (-3.63) get (-3.67)
Compliment on advertised product	36.35%	• Those shoes!! • That skirt is amazing!!!	beautiful (-2.71) skirt (-3.10) colour (-3.47) like (-3.52) babe (-3.68)

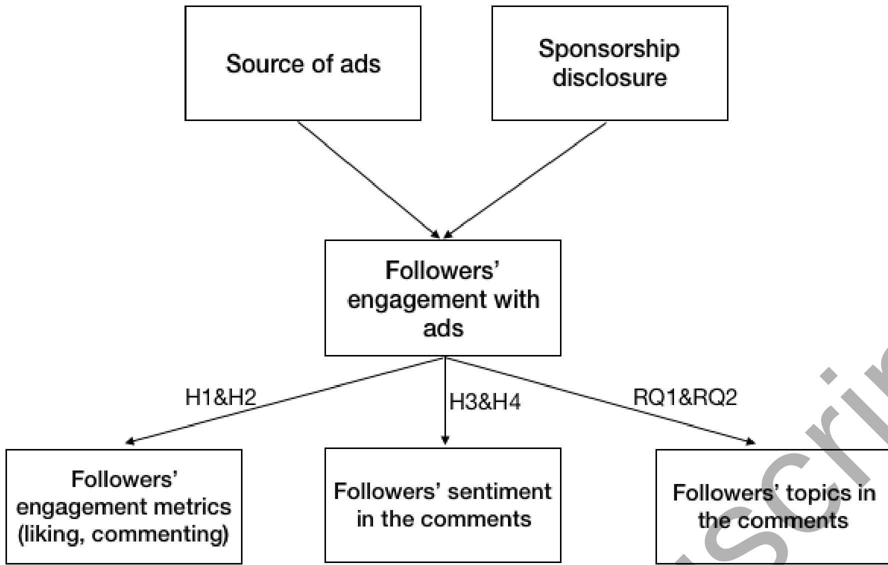

FIG. 1. Proposed Conceptual Model.

Note. Sponsorship disclosure influences followers' engagement with influencer-promoted ads only.