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How to Engage Customers on TikTok?

Completed Research Paper

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Abstract

This research investigates the effects of marketer-generated content (i.e., emotional and rational), sounds, and influencers on digital customer engagement (i.e., likes and shares) on TikTok. Data were collected from 10 Indonesian food and beverage brands. The results confirm that emotional content generates more likes and shares than rational (i.e., informational and transactional) content. Conversely, rational (i.e., informational and transactional) posts receive more likes and shares than emotional posts. Additionally, original sounds and influencers positively influence likes and shares. This study advances social media and content marketing literature in three ways. First, this research is among the first to discuss the emerging social media of TikTok. Second, this investigation is the first to examine the audio format as an element influencing engagement. Third, this study focuses on Indonesia, a developing country that is rarely investigated in content marketing studies. Practically, our research findings can guide brands in creating engaging TikTok videos.

Keywords: TikTok, customer engagement, social media, content marketing

Introduction

TikTok is a social media platform specializing in short videos of up to 10 minutes (see the explanation about TikTok in Haenlein et al. 2020). TikTok has achieved tremendous success in the social media sphere. Its global monthly active users grew substantially, from 689 million in 2020 to more than 1 billion in 2021 (Statista 2022a). Engagement also escalated 15 times from 2017 to 2019, with the need for entertainment during the COVID-19 pandemic lockdown amplifying TikTok usage (Haenlein et al. 2020). In terms of average session duration, American users spent the most time on TikTok (i.e., on average, 10.85 minutes) compared to other leading social media platforms, such as Facebook, Instagram, and Pinterest (Statista 2019). With its vast total number of users and high engagement, TikTok has manifested itself as a powerful marketing device. In its 2021 report (TikTok 2021), TikTok demonstrated that many brands (e.g., Walmart, Target, Netflix, and Applebee's) have benefited from deploying its platform for marketing. One inspiring example is that of Clinique. The hashtag #blackhoney, which is related to the brand's product line "Almost Lipstick," accrued more than 28.2 million views on TikTok. This caused a high demand for that lipstick line, and the product was sold out for several weeks at major beauty retailers, such as Sephora and Ulta.

Given such solid prospects, literature needs to provide knowledge about strategies to increase digital customer engagement (DCE) on TikTok. DCE in this research refers to "brand-related cognitive, emotional, or behavioral activity during or related to focal consumer–brand interactions" (Eigenraam et al. 2018, p. 102). We focused on the behavioral aspects of DCE, particularly likes and shares. Increasing likes is crucial for firms. High like counts indicate that firms have satisfied their customers by delivering appropriate content (Wahid and Gunarto 2022). Likes can further influence customers' purchase and product consumption intentions (Alhabash et al. 2015). Similarly, boosting the number of shares is vital in the current digital world because the more people share firms' social media posts, the more potential customers view them. In this situation, shared content can reach a massive audience at a low cost and in a short time (Tellis et al. 2019), making marketing more efficient.

When seeking factors that may enhance DCE on TikTok, scholars can depend on the notion of digital content marketing (hereafter "content marketing"). As defined by Hollebeek and Macky (2019, p. 30), content marketing is "the creation and dissemination of relevant, valuable brand-related content to current or prospective customers on digital platforms to develop their favorable brand engagement, trust, and relationships (vs. directly persuading consumers to purchase)." Thus, content marketing is about understanding customers' content preferences to satisfy them. The identification of appropriate content for customers can start by analyzing marketer-generated content (MGC), nonverbal information, and the actors transmitting the content. MGC corresponds to firms' communication shared through social media and can be categorized into emotional and rational (Dolan et al. 2019). Knowing which types of MGC can generate more DCE is imperative because it can help firms formulate strategies according to their marketing priorities (e.g., amplifying likes or shares). Nonverbal information is the media format used to communicate social media messages. Because TikTok is famous for its audio features, it is important to understand which types of sounds (i.e., original or cover sounds) can improve DCE. Actors may comprise influencers, firms' employees, celebrities, or other individuals. TikTok is overflowing with influencers, and firms have begun integrating them into their marketing strategies (Haenlein et al. 2020), creating a need to examine the value of influencers for firms' DCE on TikTok. This article aims to investigate the effects of MGC, sounds, and influencers on likes and shares on TikTok.

In analyzing DCE antecedents on TikTok, we capitalize on digital rhetoric. Fundamentally, digital rhetoric corresponds to the implementation of rhetoric strategies (i.e., *pathos*, *logos*, and *ethos*) for the examination or creation of effective communication in the digital world (Eyman 2015; Zappen 2005). *Pathos* (emotional appeal), *logos* (rational appeal), and *ethos* (communicator's character) can all appear on social media content (du Plessis 2013). Emotional and rational appeals can manifest in the form of MGC (Dolan et al. 2019). The entertaining nature of sounds on TikTok comprises *pathos*. Also, influencers as firms' communicators bear *ethos*. Rhetoric helps firms determine which resources or strategies to be used in particular situations to produce effective persuasive communication (Hamilton 2018), such as higher DCE. Grounding on this, we advance these three research questions (RQ): (RQ1) Among the two types of MGC (i.e., emotional and rational), which can generate the most likes and shares? (RQ2) Which type of TikTok sound (i.e., original or cover) can generate more likes and shares? (RQ3) Can TikTok posts displaying influencers increase likes and shares?

Indeed, content marketing and content strategy studies have inspected how MGC and nonverbal information can impact DCE. Nonetheless, the investigated platforms are limited to YouTube, Facebook, Instagram, or Twitter (Gavilanes et al. 2018; Kumar et al. 2022; Taiminen and Karjaluoto 2017; Tellis et al. 2019; Wahid and Gunarto 2022). To our knowledge, discussion about DCE antecedents on TikTok remains nonexistent. TikTok is different from its competitors. It is a short video-based platform, while YouTube and other social media are either long video-based, picture-based, or text-based. Also, more importantly, findings from prior research may be inapplicable for TikTok. Evidence has confirmed that DCE varies across social media channels. For instance, while promotional content affects likes significantly on Instagram, it has insignificant effects on likes on Facebook (Coelho et al. 2016). In the same vein, research exhibits that Facebook users prefer to comment than like, whereas customers on Instagram do vice versa (Shahbaznezhad et al. 2021). Social media is context-specific, and the absence of TikTok research summons a substantial literature gap. This content marketing study attempts to resolve this concern.

Content marketing and content strategy literature further hold several other lacunae. The most crucial one is that studies have never considered the aspect of sound in their nonverbal information construct. They merely included pictures or videos (e.g., Moran et al. 2020; Shahbaznezhad et al. 2021; Wahid and Gunarto

2022). This is a problem due to two reasons: (1) social media content can incorporate both visual and audio elements; and (2) platforms deploying sound as their ultimate weapon (e.g., TikTok) are winning on the social media battlefield (Statista 2019). The dearth of content marketing research dealing with sound on social media creates a massive theory-practice gap. As such, there is a need to study sound as one of the variables in content marketing on social media. Furthermore, scholars scarcely analyzed brands in emerging markets. Studies mostly focused on firms in developed countries such as Ireland (Moran et al. 2020), Finland (Taiminen and Karjaluoto 2017), Australia (Dolan et al. 2019), and New Zealand (Shahbaznezhad et al. 2021). Empirical results from those analyses may be inappropriate for brands in emerging nations because customer behavior on social media diverges by region and culture (Lin et al. 2017). Also, juxtaposed to developed countries, emerging markets are more challenging for social media marketers (Kim et al. 2019). Circumstances such as governmental regulations, capabilities to purchase communication devices, and broadband access prices obstruct the growth of marketing on social media in emerging nations (Ilavarasan et al. 2018). These rationales emphasize the urgency to investigate factors driving DCE on TikTok in developing countries.

Lastly, influencer studies are typically from the perspective of influencer marketing literature, and the results are less relevant for firms' content marketing. Within influencer marketing, brands aim to reach influencers' social media followers (Leung et al. 2022). Accordingly, research in this domain analyzes how brands can optimally collaborate with influencers to share branded content on those influencers' social media accounts (Tanwar et al. 2022). Evidence generally agrees that influencer marketing can benefit firms (see the discussion in Vrontis et al. 2021). Viewed from a content marketing scholarship standpoint, brands use influencers to appear on their content which is distributed through the brands' own social media accounts. Consequences of such a content marketing effort may be dissimilar from influencer marketing. Imagine Indomie (i.e., an Indonesian noodle brand) hiring Margo, an Indonesian TikTok influencer (@hola.margo) focusing on cooking and daily life. For Indomie's influencer marketing, sharing branded content on Margo's TikTok account is likely beneficial, considering she has more than 4.1 million followers and 172.9 million likes on the platform. Her followers may also have trusted her for recommendations, and there is a congruence between her niche and the brand being promoted (i.e., food). In the case of content marketing, Indomie can hire Margo to appear on its TikTok videos that are shared through the brand's own TikTok account (@indomieid). Despite the fact that Margo has a massive fanbase, the outcome of Indomie's content marketing strategy is uncertain. This is because Indomie's customers may be unfamiliar with Margo and thus deem her a regular person. Also, even if Indomie's customers know Margo, there is no guarantee that those people are Margo's fans. With such doubtful results in mind, scholars need to empirically investigate the efficacy of influencers from a content marketing perspective. Knowledge of this can guide brands on whether to deploy influencers or other actors (e.g., employees, celebrities, and chefs) on their posts to improve DCE on the brands' social media accounts. This is important because actors are necessary for firms' content creation, especially on video-based social media such as TikTok, where there is a need for someone or something to do particular activities on videos.

Our study provides five significant contributions to the literature of social media and content marketing. First, to our knowledge, our research is among the first to discuss TikTok within the theme of DCE. This will ignite further discussion regarding the topic. Additionally, given the TikTok phenomenon and the absence of academic marketing research related to the social media platform, this study bridges this practice–theory gap. Second, this research adds to the literature of content marketing and content strategy by analyzing the audio elements of media formats and their effects on DCE. This is imperative because social media content can contain both audio and visual elements, and customers may react differently to different audio formats. Third, our study is among the few to use Indonesian brands and consumers as a sample for social media analyses in developing countries. Our research shows how consumers in the biggest country in the Southeast Asian region interact with firms' content marketing on social media. Fourth, our article is also among the first to investigate the role of influencers from a content marketing stance. Fifth, we contribute to the discourse of digital rhetoric by using all three aspects of rhetoric strategies (i.e., *pathos*, *logos*, and *ethos*) in our content marketing study. Finally, in practice, insights from our findings can guide brands in creating and sharing engaging short videos on TikTok.

Conceptual Framework and Hypotheses

Digital rhetoric (Eyman 2015; Zappen 2005) serves as an overarching theoretical perspective to ground our conceptual framework in predicting the effects of MGC, sounds, and influencers on DCE in the context of TikTok. Digital rhetoric refers to the application of rhetorical strategies of persuasion—that exist in traditional rhetorical theory—for analyses or production of effective communication in the digital space (Eyman 2015; Zappen 2005). The rhetoric strategies are *pathos* (emotional appeal), *logos* (rational appeal), and *ethos* (communicator's character) (Hamilton 2018). These three approaches can all be embedded in digital content on social media for marketing (du Plessis 2013). Although there are other variables that can affect the outcomes of content marketing on TikTok, we argue that only MGC, sounds, and influencers that are highly related to the ideas of *pathos*, *logos*, and *ethos*. First of all, MGC is the heart of content marketing, and research has widely demonstrated that MGC can contain both emotional and rational (i.e., informational and transactional content) appeals (Dolan et al. 2019). Further, sounds are TikTok's main feature (Vázquez-Herrero et al. 2022). The utilization of sounds on TikTok is typically for entertaining purposes, such as dancing and lipsyncing (Haenlein et al. 2020). In this sense, sounds on TikTok contain *pathos*. Lastly, influencers crowd TikTok (Haenlein et al. 2020). When firms collaborate with them to appear on their MGC, they act as the firms' communicators. Here *ethos* comes into play, showing the communicator's persona that will be perceived by an audience (Hamilton 2018).

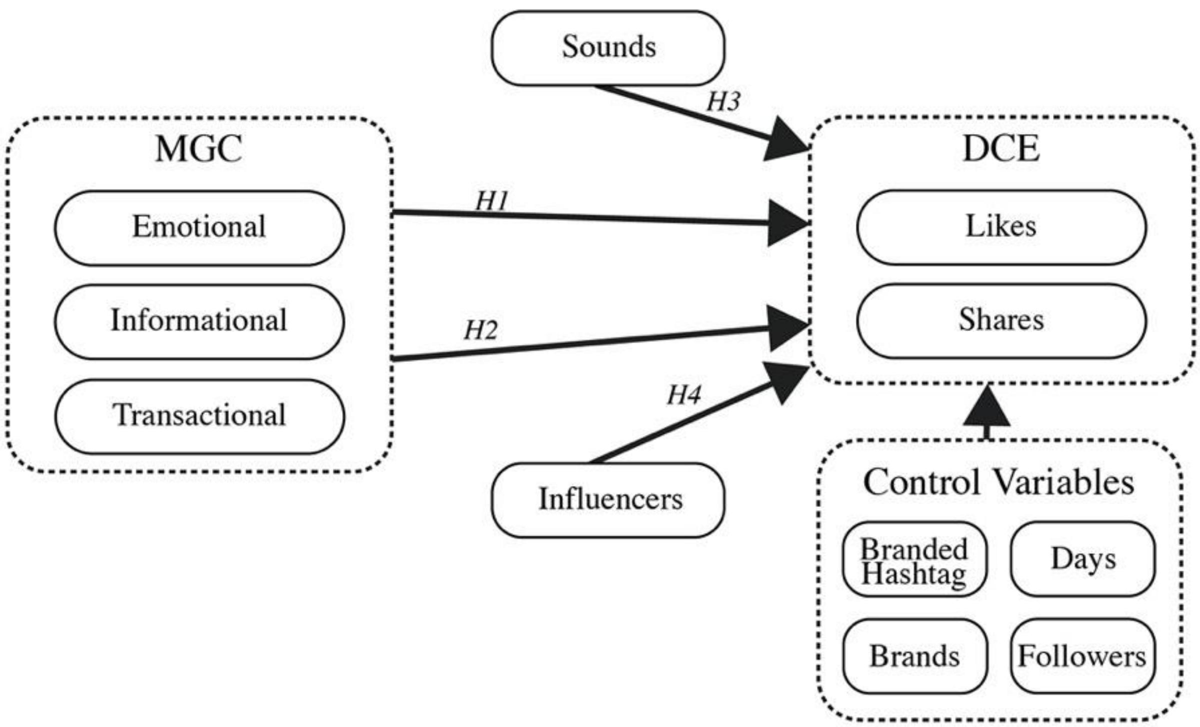

Figure 1. Conceptual Framework

Digital rhetoric avails in creating successful communication (Eyman 2015). In measuring such success on social media, firms can employ the construct of behavioral engagement (Li et al. 2021). Therefore, in this content marketing study on TikTok, DCE is the result of rhetoric strategies of *pathos*, *logos*, and *ethos*. In Eyman's (2015, p. 61) explication of digital rhetoric, the author contends that "digital rhetoric should be viewed as a field that engages multiple theories and methods rather than as a singular theory framework". Corresponding to this, we integrated digital rhetoric with dual processing theory (Kahneman 2011), music in marketing literature, warranting theory (Walther and Parks 2002), and influencer marketing literature to understand DCE antecedents on TikTok. Finally, following digital rhetoric principles (Eyman 2015), we provide the step-by-step approaches we undertook in implementing digital rhetoric in our content marketing study. First, we explored the target social media and identified the digital objects on the platform that comprise *pathos*, *logos*, and *ethos*. Second, we created data collection procedures according to the identified rhetoric strategies. Third, we collected and analyzed the data. Fourth, after generating results, we proposed our analysis's theoretical and practical values. Figure 1 visualizes our conceptual framework.

Digital Customer Engagement

Behavioral DCE is one of the primary outcomes of content marketing (Hollebeek and Macky 2019) and rhetoric strategies (du Plessis 2013). Our dependent variable was behavioral DCE, consisting of likes and shares. In conceptualizing this DCE, we referred to Dolan et al.'s (2019) research, where DCE was divided based on the level of engagement (e.g., passive or active). In this study, we considered likes low DCE and shares high DCE. The logic behind this corresponds to the number of activities executed by customers when liking and sharing social media content. To like a post on TikTok, customers simply need to double-tap the video or tap the heart icon on the right panel. To share TikTok videos, customers need to perform more actions and cognitive processes. For example, when customers find a TikTok video worth sharing to their networks on WhatsApp, they must (1) tap the share button on the right panel, (2) choose WhatsApp among several applications and media available, (3) consider and pick the person or people who will receive the shared content, and (4) press the send button on WhatsApp.

We included only likes and shares and excluded comments because increased likes and shares signify the success of content marketing strategies. High like counts mean that the content is appropriate for target customers (Wahid and Gunarto 2022), whereas high numbers of shares indicate that the content can instigate electronic word of mouth and hence may attract future customers to view social media posts (Tellis et al. 2019). Therefore, insights into the factors driving likes and shares are practical: firms can implement the guidelines in a straightforward manner, and the increased likes and shares will likely benefit firms. Conversely, a significant number of comments is unnecessarily a good indicator for firms because they comprise sentiment. While positive sentiment in social media comments can improve marketing outcomes, its negative counterpart can jeopardize brands (Meire et al. 2019). Therefore, providing guidelines to enhance comments without sentiment analysis can be misleading. Given such a potential error, and because we disregarded sentiment analysis in our study, we only used likes and shares.

Marketer-Generated Content

MGC can contain emotional and rational appeals. The former appeal can manifest as emotional content, while the latter can appear as informational and transactional content (Dolan et al. 2019). We defined emotional content as affect-laden social media messages intended to stimulate emotional or sensory responses (Meire et al. 2019). Informational content is in posts conveying information, either related or unrelated to firms' offerings, in a non-promotional fashion (Wahid and Gunarto 2022). Germane to transactional content, it has several other names in social media literature, such as remunerative, promotional, and commercial (Shahbaznezhad et al. 2021). In this research, we used the term "transactional" to represent content that comprises transaction-loaded communication, such as sales, promotions, giveaways, monetary incentives, and donations.

Rhetoric concerns which strategies need to be used for effective communication in specific situations (Hamilton 2018). In the context of this study, we investigated which of the rhetoric approaches (i.e., *pathos* in the emotional content or *logos* in the informational and transactional content) is the most appropriate to be embedded on MGC for the enhancement of each of the DCE (i.e., likes and shares). In doing so, we integrated digital rhetoric (Eyman 2015; Zappen 2005) with dual processing theory (Kahneman 2011). Fundamentally, dual processing theory explains how individuals process thoughts through two different channels: System 1 and System 2. In System 1, reasoning is more implicit, unconscious, automatic, and typically connected with strong emotional ties. In System 2, the process of thoughts is more explicit, conscious, controlled, and usually dependent on attitudes and judgments. Studies have found that the way people process information affects their economic behavior (Alós-Ferrer and Strack 2014). In social media and content marketing research, Dolan et al.'s (2019) investigation of Facebook discovered that (1) when exposed to emotional content, customers engage passively (e.g., viewing), and (2) when encountering informational and transactional social media posts, customers engage actively (e.g., sharing). Dolan et al. (2019) argued that emotional content requires marginal thinking and thus activates reasoning through System 1. Because the process of thought is unconscious and weak, emotional content is unable to stimulate customers to be more active in performing DCE. By contrast, informational and transactional messages operate reasoning through System 2. Customers expend effort on examining and understanding social media posts. This use of high cognition toward informational and transactional content transmits to behavioral DCE, in which customers make conscious and deliberate decisions when engaging with firms (e.g., thinking about whether to share/who will receive the posts and sharing the posts).

The argument above may also apply to this study. Emotional TikTok posts are likely to receive more likes than their informational and transactional equivalents. This is because the processing of such messages transpires in System 1. In this condition, reasoning is unconscious, making the behavior less willful (e.g., liking by simply double-tapping a phone screen). Conversely, informational and transactional posts plausibly receive more shares than emotional content. Informational and transactional TikTok videos demand that customers discharge high cognition because the thought processing is in System 2. Such conscious thinking may also influence customers to perform deliberate behavioral DCE, such as sharing. Therefore, we hypothesized the following:

H1. Emotional content (i.e., containing *pathos*) generates more likes than informational and transactional content (i.e., containing *logos*).

H2. Informational and transactional content (i.e., containing *logos*) generate more shares than emotional content (i.e., containing *pathos*).

Sounds

Nonverbal information has been the focus of the content marketing literature. However, the discussion thus far has focused on its visual aspect (e.g., Shahbaznezhad et al. 2021; Wahid and Gunarto 2021). We specifically analyzed sounds to fill this gap. We conceptualized sounds as any audio format (e.g., songs, dialogues, monologues, and instrumental music) used by firms in their social media content that is divided based on the source—original or cover sounds. Original sounds are those audio communications created in-house by firms for their social media posts, and cover sounds correspond to audio pieces owned by other people or creators and deployed by firms for their social media content.

The use of sounds on TikTok is mostly for entertainment purposes. Because all elements in communication that elicit emotional responses are deemed to have *pathos* (Hamilton 2018), sounds then comprise emotional appeal. Digital rhetoric allows researchers to analyze which aspect of rhetoric methods can result in the most effective communication (Eyman 2015). Underpinned by this, we aimed to understand which sounds can generate higher DCE: original or cover sounds. In this study, we predicted that TikTok videos containing original sounds would receive more likes and shares than those using cover sounds. In proposing this hypothesis, we drew on the advertising literature on music, which states that firms need to consider music–brand congruity when applying music to achieve the desired marketing objectives, and that music sources can shape such congruity (Lantos and Craton 2012). Music and lyrics written by firms for their own commercials are more congruent than those created by someone else, and they already exist prior to the release of the pertinent advertisement. Firms can adjust the tune and words in the music with their brands and intended messages, and such adjustments are more restricted when sound pieces are already available on the market. Empirical evidence confirms that music composed particularly for a commercial improves marketing outcomes (e.g., recall) (North et al. 2004; Tom 1990; Yalch 1991). Likewise, high message–music congruity leads to greater message and brand name recall (Kellaris et al. 1993; Oakes 2007). We propose similar reasoning for this DCE study. Analogous to music in advertisements, sounds for marketing purposes on TikTok can originate from either other users (i.e., cover sounds) or in-house (i.e., original sounds). Cover sounds are prone to being incongruent with brands for several reasons, such as their worldwide nature and the varying meanings carried by such sounds. Imagine a person from England accidentally seeing a TikTok post from Lemonilo (i.e., an Indonesian food brand) because the content is linked to a Justin Bieber song. Either due to the incongruity of location or the language used for Lemonilo's content, the English person is likely to ignore the post. Additionally, cover sounds or music may irritate customers (Lantos and Craton 2012). Consider a Lemonilo's TikTok video displaying a person talking: when cover sounds are embedded in the content, it may distract customers from understanding it and eventually may cause irritation toward the video. By contrast, original sounds can match firms' TikTok videos with their messages and allow firms to focus on talking on their TikTok posts without adding cover sounds as background music. Such strategies can enhance brand–sound congruity and diminish distraction. This may eventually promote more likes and shares. Bearing this in mind, we expected the following:

H3. TikTok posts with original sounds generate more likes and shares than those with cover sounds.

Influencers

Influencers are one type of actor that can help brands achieve their goals (Haenlein et al. 2020; Li et al. 2021). Influencers in this research refer to "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). As humans, influencers have *ethos*. In communication, *ethos* is substantial because it relates to the *desirable character* of the communicators (Hamilton 2018). People with high *ethos* values can easily persuade others (Eyman 2015). In this study, we compared the capability of influencers in stimulating DCE with other actors that appeared on firms' TikTok videos. In conducting this endeavor, we drew on digital rhetoric (Eyman 2015; Zappen 2005), warranting theory (Walther and Parks 2002), and influencer marketing literature.

Warranting theory advances that, in computer-mediated communication, other endorsement yields more persuasive power and positive effects than self-endorsement. Walthers et al. (2009) confirmed this theory in the Facebook environment. In their experiment, participants viewed statements about a person's physical attractiveness (i.e., statements on friends' comments versus statements on self-comments). The results proved that perception of attractiveness is stronger through friends' comments than through self-claim on self-comments. In Jin's (2018) study, research participants were exposed to Paris Hilton-owned brands and product lines advertised on Facebook. The conditions were other endorsement (i.e., advertisement on a regular person's Facebook profile) versus self-endorsement (i.e., advertisement on Paris Hilton's personal Facebook page). The findings showed that trustworthiness and goodwill were higher for other endorsements than for self-endorsement conditions. This indicates that firms' content shared through the firms' own social media accounts showing any other actors (e.g., celebrities and influencers) will generate higher DCE than the posts displaying firms' own actors (e.g., owners and employees). Further, looking deeper into these types of actors, we predicted that influencers can stimulate higher DCE than other actors. Influencer marketing literature demonstrates that influencers are more persuasive than other actors (e.g., celebrities) for two reasons: (1) they are experts in specific areas; and (2) people consider them as peers because they look like "normal people" (Leung et al. 2022; Lou and Yuan 2019; Vrontis et al. 2021). In this sense, influencers have higher *ethos* values than other actors. Therefore, we anticipated the following:

H4. TikTok posts displaying influencers generate more likes and shares than those displaying other actors.

Methods

Research Contexts

We focused on Indonesia for this TikTok study. With a population of more than 270.2 million people (Statista 2021), Indonesia also has the second-largest TikTok audience in the world, after the United States, with approximately 92 million active users (Statista 2022b). Within Indonesia, we concentrated on the food and beverage (F&B) sector owned by locals (i.e., Indonesian companies or individuals) to reduce potential confounding effects caused by the contextual nature of social media. Evidence has shown that content marketing and DCE are dependent on industries' and brands' countries of origin (see e.g., Kim et al. 2019; Lin et al. 2017; Schultz 2017; Wahid and Gunarto 2021). The use of F&B as our sample was based on our exploration of TikTok prior to data collection. Initially, we gathered Indonesian brands that were active on TikTok and listed those that met the following criteria: (1) owned by Indonesian firms or individuals and (2) verified by TikTok (i.e., possessing the blue checkmark). This listing effort generated 52 brands, where F&B was the most dominant category (n = 10).

Coding Variables, Procedures, and Sampling

Following previous DCE literature on video-based social media (e.g., Tellis et al. 2019), we conducted content analysis through manual coding to model our MGC, sounds, and influencer variables. We began by preparing a set of coding instructions to capture the dimensions of each construct. We first documented content types shared specifically by Indonesian F&B brands on TikTok. This process involved analyzing and noting the styles and messages embedded in approximately 100 videos and video captions of those F&B brands, which resulted in 20 content topics. Additionally, we prepared the guideline to check the origin of a sound in a TikTok video, as follows: (1) tap on the sound icon at the bottom of a video; (2) examine the page offering the details of the sound—first, second, and third lines showing the sound title, the owner of the sound, and the total videos using the sound, respectively; and (3) focus on the second line and input the sound (a) as original if the owner of the sound created the video or (b) as a cover if another creator owns the sound. We also provided a precept to capture the influencer variable. When we inspected the TikTok posts, we found that although several Indonesian influencers were familiar to us, others were difficult to identify. For unidentifiable influencers, we created the following coding instructions: (1) check the caption to see whether there is an account being tagged in the video; (2) if yes, tap the account; (3) look at the number of followers; (4) if the TikTok account has at least 10,000 followers, then document as influencer content; and (5) if no account is tagged in the video caption or the follower count is less than 10,000, input as non-influencer content. We used the 10,000-follower threshold due to the vagueness of rules in both industry and academic research about influencer categories based on followers (see the discussion of mega, macro, micro, and even nano influencers in Haenlein et al. 2020). We also mentioned that influencers are people with large follower counts on social media who gain fame exclusively via social media. This means that the influencer construct excludes certain influential individuals, such as singers, actors, athletes, models, chefs, and others. Although we neglected these well-known personalities in our model, we recorded them as "celebrities" in our data collection process to anticipate their potential influence on our regression results. Additionally, while the sound and influencer constructs are mutually exclusive, the 20 topics of MGC are non-mutually exclusive. This denotes that one TikTok post can have one or more topics. For instance, a TikTok video can contain a sketch and a promotion simultaneously. Such treatment is similar to other content marketing and social media studies (e.g., Wahid and Gunarto 2021; Weiger et al. 2018). As a further note regarding the MGC construct, our focus was to inspect the presence of the MGC types and their influence on DCE. In other words, all that matters was whether the topics was present or absent (i.e., we coded MGC topics as present = 1; absent = 0). Considering this, we ignored the factor of time when collecting the data. To illustrate, we recorded the content as information regardless of whether it appeared only for five seconds or one minute. Table 1 exhibits the details of our constructs.

Construct	Description
MGC	
Emotional	
Dance	Person(s) dancing (e.g., a video of Nutrisari [@nutrisari] displaying a woman dancing to its #TemanHealing challenge)
Singing	Person(s) singing a song, either original or cover songs (e.g., a man singing an original song mentioning Aqua [@sehataqua])
Humor	Videos aiming to stimulate laughter (e.g., an influencer delivering a dad joke on Tropicana Slim's account [@tropicanaslim])
Storytelling	Narrating a story related to products, owners of the brands, or customers (e.g., a customer narrating her daily life and mentioning her visit and experience in Kopi Kenangan's [@kopikenangan.id] shop)
Sketch	Person(s) acting (e.g., a group of friends acting as if they are on a holiday while consuming Chitato [@mychitato])
Lifestyle	Videos displaying the lifestyles of brands' employees, customers, or people in general (e.g., an influencer showing his lifestyle to maintain his health by consuming Aqua [@sehataqua] and swimming)
Relatable facts	Content delivering life facts relating to particular groups of people (e.g., content of Lemonilo [@lemonilo] showing how the eating styles of women and men differ)
Sympathy and sadness	Videos aiming to stimulate the feelings of sadness and sympathy (e.g., content of Aqua [@sehataqua] showing an old and hardworking man)
Encouraging	Content that is encouraging or giving good life lessons (e.g., content of Kapal Api [@kapalapi_id] thanking people for their existence and hard work and inviting them to take a rest)
Interaction with customers/people	Brands responding to customers' or people's comments (e.g., Bittersweet by Najla [@bittersweetbynajla] responding to its customers' comment about its birthday cake)

Games	Person(s) playing a game in the content (e.g., content of Chitato [@mychitato] showing two people playing the "Don't Spill the Snack" game)
Informational	
Information	Delivering information or education unrelated to products (e.g., a content of Kapal Api [@kapalapi_id] showing an influencer giving lessons about creating a sustainable business)
Appetite-Arousal	Content displaying customers or person(s) reviewing the taste of the food or drink offered by brands (e.g., two people eating the product of Lemonilo [@lemonilo] saying "the noodle is creamy and yummy" with a fully satisfied expression)
Behind-the-Scene	Videos displaying the process of making a product offered by brands (e.g., Bittersweet by Najla [@bittersweetbynajla] showing the process of making a customized birthday cake for its customer)
Tutorial	Videos showing the step-by-step execution of particular tasks (e.g., an influencer demonstrating how to create a quality TikTok video on Aqua's [@sehataqua] account)
Transactional	
Product	Displaying (through subtitles or captions) or speaking (through a voice) about product features and product newness (e.g., Aqua [@sehataqua] informing its new packaging)
Promotion	Offering promotion either through spoken or written communications (e.g., Kopi Kenangan [@kopikenangan.id] informing its Rp55,000 breakfast promotion)
Competition	(1) Informing challenges or competition with rewards (rewards can be in the form of products, money, or others); (2) Content be in the form of invitation or announcement of winners; (3) Customers are obliged to do something to win the competition or challenges (e.g., Greenfields [@greenfields.id] announcing the winners of its #YogurtBikinSeger TikTok challenge)
Giveaway	(1) Brands giving free products to customers or followers on TikTok; (2) Unlike competition, there is no requirement to do something in order to receive free products from brands (e.g., Bittersweet by Najla [@bittersweetbynajla] giving free cakes for its TikTok followers)
Donation	Brands facilitating donations for a particular group of people (e.g., Aqua [@sehataqua] inviting its customers to join its donation program to help small and medium enterprises affected by the COVID-19 pandemic)
Original sounds	(1) Audio communications created in-house by firms for their social media posts; (2) The base line for original sounds is *cover sounds* which are audio pieces owned by other people or creators and deployed by firms for their social media content
Influencers	(1) “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); The baseline for influencers is *other actors* which are those non-influencers (e.g., celebrities and unknown individuals)
Control variables	
Branded Hashtags	(1) Hashtag created by brands relating to their brands or products (e.g., #RasanyaPopMarkopop by Indomie and #lemonilo by Lemonilo; (2) The presence of branded hashtag(s) is the variable measured in the models, and the absence of branded hashtag(s) is the baseline
Days	The posting times of TikTok videos where *weekdays* is the variable included in the models and *weekends* is the baseline
Followers	Numbers of followers owned by each brand
Brands	The 10 brands sampled in the study

Table 1. Description of Constructs

After the coding instructions were ready, the next step was to train the coders. Two Indonesian coders participated in the data collection process. They were paid and blinded to the purpose of our study. The training was conducted online using Zoom, and we recorded the video training. When questions arose, coders could watch the video again, read the written version of the instructions carefully, or ask us directly. The two coders collected the data in two phases. In the first phase, we aimed to ascertain reliability, and the coders input 130 TikTok posts. We analyzed the data and found that the Cohen's kappa value was 0.984, which is almost perfect. These excellent reliability results surfaced because the training was intensive, ongoing support for clarification was available, the coders had coding experience in analogous social media research, and the coders were heavy users of TikTok. The high reliability allowed us to advance to the second phase, in which the two coders collected the remaining data. Due to limited published data, the coders collected all the posts available from the 10 F&B brands. The endpoint of the data collection was February 28, 2022, and the total dataset was 1,716.

Next, we performed a data-cleaning procedure. Our dependent variable data were highly skewed (i.e., 30% with less than 100 likes and 19% with more than 100,000 likes; 42% with less than 10 shares and 8% with more than 1,000 shares). This situation resembles the study of Tellis et al. (2019). Including all the data in the regression analyses (n = 1,716) would produce less informative results, as the data contained either too few or too many likes and shares. Therefore, we followed Tellis et al. (2019) by conducting stratified sampling. We divided our data into four groups based on their data distributions: 0 to < 25%; 25% to < 50%; 50% to < 75%; and 75% or more. We then took 300 random samples from each group, resulting in 1,200 data (Aqua = 41; Bittersweet by Najla = 385; Chitato = 37; Greenfields = 2; Indomie = 48; Kopi Kapal Api = 30; Kopi Kenangan = 119; Lemonilo = 413; Nutrisari = 86; Tropicana Slim = 39).

We further checked our independent variables. The data of 20 MGC types were inadequate for independent analysis (e.g., only eight posts contained heartwarming topics). Thus, following extant social media studies (e.g., Meire et al. 2019; Shahbaznezhad et al. 2021), we grouped MGC into three primary characteristics: emotional, informational, and transactional. To be included in the emotional category, the content needed to be emotional, arousing, persuasive, engaging, or entertaining. For informational content, posts needed to be informative but in a non-promotional manner. Finally, to be categorized as transactional content, videos needed to focus on sales, promotions, giveaways, monetary incentives, or donations. The sound and influencer constructs had no adjustments. For the celebrity variable, only a small amount of content was delivered by celebrities. Therefore, we mixed the category with other actors and employed the construct "other actors" as the base variable for influencers.

Data Analysis

Our sample of F&B brands may have within-individual and between-individual variances. Initial testing indeed evidenced that there was a significant intraclass correlation in our brands' variables. To analyze such data, a mixed-effect model is more efficient than ordinary least squares regression (Garson 2014a). Accordingly, our mixed-effect models for predicting likes and shares were as follows:

$$\begin{aligned}\log(\mathrm{DCE}) = \alpha_{\mathrm{brand}} &+ \beta_1 \times emotional + \beta_2 \times informational + \beta_3 \times transactional + \beta_4 \times sounds \\ &+ \beta_5 \times influencers + \beta_6 \times branded\ hashtag + \beta_7 \times days + \beta_8 \times log\ (followers) \\ &+ \varepsilon\end{aligned}$$

Log (DCE) is the logarithmic of likes and shares to account for the skewness of the data. The α and β are the estimated coefficients, while ε is the error term. We modeled likes and shares differently. We suppressed the subscripts of the individual TikTok posts for ease of reading and included the constructs of emotional, informational, and transactional content. We also added sounds (original sounds = 1; cover sounds as the baseline = 0) and influencers (influencers = 1; other actors as the baseline = 0) variables. In addition, as previously mentioned, there was significant intraclass correlation in the brands' constructs; thus, we controlled the effects of brands by using two approaches. First, we appended a brand-level intercept (α_{brand}) to consider unobserved heterogeneities in brand characteristics that might affect DCE. Second, we included the logarithmic brands' followers because some brands were more popular than the others in our dataset. Additionally, evidence has shown that branded hashtags can influence DCE (Kumar et al. 2022); hence, we controlled branded hashtags (present = 1; absence of branded hashtags as the baseline = 0). Lastly, because posting times can influence DCE (Kanuri et al. 2018; Wahid and Gunarto 2022), we also considered the posting times in our dataset (weekdays = 1; weekends as the baseline = 0). Table 2 displays the descriptive statistics of our independent categorical variables.

Parameters	n	%	VIF - Likes	VIF - Shares
emotional	599	49.9	1.106	1.112
informational	330	27.5	1.079	1.076
transactional	1060	88.3	1.338	1.347
original sounds (baseline: cover sounds)	810 (390)	67.5 (32.5)	1.290	1.307
influencers (baseline: other actors)	293 (907)	24.4 (75.6)	1.107	1.108
Control variables				
branded hashtag (baseline: non-branded hashtag)	889 (311)	74.1 (25.9)	1.031	1.027
day-weekdays (baseline: weekends)	959 (241)	79.9 (20.1)	1.023	1.024

Table 2. Descriptive Statistics of the Independent Variables

Results

Table 3 presents the mixed-effect model results. The findings show that emotional content generated more likes (0.385, $p < 0.01$) than informational and transactional content (informational: 0.306, $p < 0.01$; transactional: 0.369, $p < 0.01$). By contrast, informational and transactional content (informational: 0.211, $p < 0.01$; transactional: 0.389, $p < 0.01$) received more shares than emotional content (0.195, $p < 0.01$). Accordingly, this study accepts H1 and H2. In addition, TikTok posts with original sounds generated more likes (0.193, $p < 0.01$) and shares (0.127, $p < 0.05$) than those with cover sounds. Similarly, TikTok videos delivered by influencers generated more likes (0.259, $p < 0.01$) and shares (0.155, $p < 0.01$) than those by non-influencers. Therefore, this study accepts H3 and H4.

	Model 1 - Likes			Model 2 - Shares		
Parameters	Estimate	Std. Error	F	Estimate	Std. Error	F
emotional	0.385**	0.058	43.000**	0.195**	0.047	16.809**
informational	0.306**	0.063	23.545**	0.211**	0.051	17.126**
transactional	0.369**	0.098	14.125**	0.389**	0.077	25.444**
original sounds (baseline: cover sounds)	0.193**	0.064	8.851**	0.127*	0.052	5.898*
influencers (baseline: other actors)	0.259**	0.066	15.274**	0.155**	0.053	8.551**
Control variables						
branded hashtag (baseline: non-branded hashtag)	-0.052	0.063	0.683	-0.082	0.051	2.634
day-weekdays (baseline: weekends)	0.180**	0.066	7.444**	0.083	0.054	2.333
log followers	1.208**	0.227	28.411**	0.677**	0.165	16.901**

Table 3. Mixed-Effect Model Results

Note: **$p < 0.01$; *$p < 0.05$

We also conducted robustness tests for our models. According to Garson (2014b), a mixed-effect model is the most robust when its Akaike's Information Criterion (AIC) and Schwarz's Bayesian Criterion (BIC) values are the lowest compared to other mixed-effect models. We compared our mixed-effect models with others in which interaction effects between variables were included. As displayed in Table 4, our model (i.e., Model 4) had the lowest AIC values (likes = 3,197.101; shares = 2,386.191) and BIC (likes = 3,207.266; shares = 2,396.187) compared to Model 1 (AIC likes = 3,200.750; AIC shares = 2,393.427; BIC likes = 3,210.905; BIC shares = 2,403.411), Model 2 (AIC likes = 3,197.841; AIC shares = 2,389.329; BIC likes = 3,208.001; BIC shares = 2,399.319), and Model 3 (AIC likes = 3,200.406; AIC shares = 2,390.510; BIC likes = 3,210.566; BIC shares = 2,400.500). Notably, due to these results, we can only discuss the direct effects of our independent variables and must neglect the interaction effects between variables (e.g., emotional content x influencers).

	Model 1		Model 2		Model 3		Model 4	
	Likes	Shares	Likes	Shares	Likes	Shares	Likes	Shares
Parameter	Est. (Std. Error)	Est. (Std. Error)	Est. (Std. Error)	Est. (Std. Error)	Est. (Std. Error)	Est. (Std. Error)	Est. (Std. Error)	Est. (Std. Error)
emotional	0.476** (0.122)	0.196* (0.099)	0.415** (0.068)	0.245** (0.055)	0.440** (0.116)	0.139 (0.093)	0.385** (0.058)	0.195** (0.047)
informational	0.329* (0.133)	0.158 (0.106)	0.349** (0.074)	0.211** (0.060)	0.272* (0.125)	0.152 (0.099)	0.306** (0.063)	0.211** (0.051)
promotional	0.392* (0.171)	0.312* (0.135)	0.519** (0.144)	0.443** (0.114)	0.237 (0142)	0.251* (0.111)	0.369** (0.098)	0.389** (0.077)
sounds	0.507** (0.167)	0.311* (0.136)	0.507** (0.166)	0.319* (0.135)	0.191** (0.065)	0.124* (0.052)	0.193** (0.064)	0.127* (0.052)
influencer	0.230 (0.159)	0.027 (0.128)	0.260** (0.066)	0.158** (0.053)	0.214 (0.159)	0.013 (0.128)	0.259** (0.066)	0.155** (0.053)
emotional x sounds	-0.177 (0.125)	-0.194 (0.101)	-0.172 (0.124)	-0.197 (0.101)	-		-	
informational x sounds	-0.205 (0.141)	-0.054 (0.112)	-0.211 (0.140)	-0.064 (0.112)	-		-	
promotional x sounds	-0.362* (0.179)	-0.179 (0.142)	-0.338 (0.178)	-0.158 (0.141)	-		-	
emotional x influencer	-0.081 (0.128)	0.059 (0.103)	-		-0.075 (0.128)	0.069 (0.103)	-	
informational x influencer	0.037 (0.141)	0.071 (0.113)	-		0.058 (0.141)	0.081 (0.112)	-	
promotional x influencer	0.269 (0.175)	0.247 (0.138)	-		0.248 (0.174)	0.232 (0.137)	-	
branded hashtag	-0.063 (0.063)	-0.091 (0.051)	-0.056 (0.063)	-0.084 (0.051)	-0.059 (0.063)	-0.088 (0.051)	-0.052 (0.063	-0.082 (0.051)
weekdays	0.179** (0.066)	0.077 (0.054)	0.182** (0.066)	0.080 (0.054)	0.178** (0.066)	0.079 (0.054)	0.180** (0.066)	0.083 (0.054)

log followers	1.209** (0.227)	0.677** (0.164)	1.205** (0.227)	0.674** (0.163)	1.211** (0.227)	0.679** (0.166)	1.208** (0.227)	0.677** (0.165)
AIC	3200.750	2393.427	3197.841	2389.329	3200.406	2390.510	3197.101	2386.191
BIC	3210.905	2403.411	3208.001	2399.319	3210.566	2400.500	3207.266	2396.187

Table 4. Robustness Test Results

Note: **p < 0.01; *p < 0.05

Discussion

This research investigated the effects of MGC, sounds, and influencers on likes and shares on TikTok. Regarding RQ1, we determined that emotional content can stimulate more likes than its informational and transactional counterparts. We also showed that informational and transactional content can induce more shares than emotional content. These findings align with prior research by Dolan et al. (2019). Connecting the findings with digital rhetoric, *pathos* is more effective than *logos* in attracting likes, and vice versa in improving shares. Pertaining to RQ2, we discovered that original sounds generated more likes and shares than cover sounds. As explained by the advertising literature on music (Kellaris et al. 1993; North et al. 2004; Oakes 2007; Yalch 1991), the message–music congruity embedded in original sounds may play a role in the findings of our study. In the case of RQ 3, we found that TikTok posts displaying influencers received more likes and shares than those displaying non-influencers. This is similar to previous research by Lou et al. (2019) and may relate to warranting theory (Walther and Parks 2002), where content conveyed by influencers is less susceptible to manipulation, causing increased DCE. The insight also suggests that influencers' *ethos* values are higher than other actors' (e.g., celebrities), and thus messages with influencers as communicators are more persuasive.

Theoretical Contributions

Our study offers three contributions to the literature on social media and content marketing. First, our research is among the first to analyze the DCE on TikTok. Previous studies have focused on Facebook, YouTube, Twitter, Instagram, Renren, or Sina Weibo (Chung et al. 2020; Gao and Feng 2016; Taiminen and Karjaluoto 2017; Tellis et al. 2019; Wahid and Gunarto 2022). Social media literature has shown that DCE and customer behavior toward content marketing can vary across channels. With this in mind, we provide preliminary findings about content marketing and DCE on a short video-based social media platform (i.e., TikTok). This study also responds to many calls from prior research (e.g., Dwivedi et al. 2020; Li et al. 2021) to investigate emerging social media and continually bridge the practice–theory gap in this fast-changing world of social media. Second, we expand the discussion regarding the role of nonverbal information in enhancing DCE by inspecting sounds. This is substantial for social media and content marketing literature, as previous studies have merely focused on the visual aspect of nonverbal information. In addition, marketing scholars (e.g., Bruner 1990) have predicted that music-related research will be common in the future. In the social media domain, our study is among the first to investigate the role of music in influencing marketing objectives. Third, we enriched social media and content marketing studies by using Indonesia as a sample representing developing countries. The nation is massive, with the fourth largest population in the world and the largest in Southeast Asia. Despite its size, Indonesia has been neglected by scholars. Given that consumer behavior on social media differs across geography and culture (Ilavarasan et al. 2018; Lin et al. 2017), our research presents important insights into how 92 million Indonesian TikTok users engage with content marketing. Fourth, we analyzed the role of influencers from the perspective of content marketing. This is different from many studies that typically discussed influencers through the influencer marketing literature lens. Fifth, we contribute to the emerging discourse of digital rhetoric. Scholars of digital rhetoric (Eyman 2015; Zappen 2005) have called for studies from other fields to engage with the topic. We responded to this, by employing digital rhetoric in the content marketing domain. Also, previous research (du Plessis 2013) that utilized digital rhetoric on social media marketing only focused on one aspect of rhetoric strategies (i.e., *logos*) and asked other scholars to implement *pathos* and *ethos* in their analysis. In this content marketing study on TikTok, we applied all the strategies of persuasion (i.e., *logos*, *pathos*, and *ethos*). Furthermore, for easier replication and further discussion of digital rhetoric in the content marketing sphere, we provided the step-by-step approaches we have undertaken in the application of digital rhetoric in our study (see in the *Conceptual Framework and Hypotheses* section).

Practical Implications

Increasing DCE is important for brands. Extensive likes indicate that a content marketing approach is successful and can affect customers' purchase and product consumption intentions (Alhabash et al. 2015). Also, shares on social media can contribute to more efficient marketing efforts. The more people share firms' social media posts, the more potential customers view them. Shared content can reach a massive audience at a low cost and in a short time (Tellis et al. 2019). The findings of this study reveal how MGC, sounds, and influencers can influence DCE. These insights can aid firms in formulating content marketing strategies on TikTok. If firms' objectives include increasing likes, they should invest more on creating quality emotional content. Our data collection process identified eleven types of emotional content. Firms can formulate their TikTok videos according to these emotional content variations. For instance, one of the brands in our sample (i.e., Chitato) created a comedy sketch about a group of friends on a holiday. Another alternative, as exhibited by Tropicana Slim, firms can share dad jokes or any other humor that relates to their customers. On the other hand, if firms' priorities include increasing the number of shares, then they need to distribute quality informational and transactional videos. To illustrate, Bittersweet by Najla often creates behind-the-scene videos about the process of making cakes (i.e., informational content). Also, Kopi Kenangan frequently offers promotional videos on its TikTok account (e.g., 30% discounts). Brands can follow these approaches in formulating their informational and transactional MGC. Additionally, firms need to limit themselves to using cover sounds because the original sounds generate more likes and shares on TikTok. Finally, on a video-based social media platform such as TikTok, the appearance of actors is almost a necessity. In choosing the type of actors, firms encounter many choices (e.g., influencers, firms' employees, and celebrities). Our results show that the person(s) appearing on firms' MGC should be influencers rather than other actors. The employment of influencers can significantly increase engagement on TikTok. Based on our sample, firms can hire influencers to perform various activities on the content shared by the firms' social media accounts, such as dancing, trying and reviewing the products, telling jokes, and participating in games.

The above guidelines should be considered cautiously. Countries, product levels of engagement, and social media platforms can cause varying DCE (see e.g., Schultz 2017; Wahid and Gunarto 2021). Therefore, the generalizability of the results may only apply to local firms in Indonesia offering low-involvement products (e.g., food) and using TikTok for content marketing.

Limitations and Future Research

Despite our efforts to discover which factors drive DCE on TikTok, our research has several limitations. First, we neglected the interaction effects between the constructs. This is because the inclusion of such effects reduces the robustness of our models. Individually, sounds and actors may moderate the effects of MGC on DCE (see e.g., Han et al. 2020). Future research could consider such interaction effects to produce more meaningful and practical insights. Second, our data collection procedures employed human coding. Future research may use machine coding processes to generate more reliable results. Third, although we provide preliminary insights into the role of sounds in enhancing DCE on TikTok, these insights cover only the surface of this topic. Future studies may discuss sounds in more profound ways, such as by analyzing the potential effects of music popularity on TikTok, music genres, or local versus international sound creators. Fourth, as previously mentioned, content marketing and DCE on social media are highly contextual. This study incorporated a sample from Indonesia and low-level involvement products. Future research may explore other samples (e.g., India and high-involvement products).

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