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Fostering consumer engagement with marketer-generated content: the role of content-generating devices and content features

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Abstract

Purpose – This research explores the impacts of content-generating devices (mobile phones versus personal computers) and content features (social content and achievement content) on consumer engagement with marketer-generated content (MGC) on social media. It also examines these factors' interaction effects on consumer engagement.

Design/methodology/approach – The study analyzed MGC that 210 companies had posted to Sina Weibo over three years, testing the study's proposed model with negative binomial regression analysis.

Findings – The study's results show that MGC generated via mobile phones attracts more consumer engagement than MGC generated via personal computers. MGC with more social features attracts more consumer engagement, whereas MGC with more achievement features reduces consumer engagement. The authors also found that MGC with more social features generated via mobile phones and MGC with more achievement features generated via personal computers lead to more consumer engagement due to the congruency of the construal level of psychological distance.

Originality/value – This research enriches the literature by exploring the effects of content-generating devices and content features on consumer engagement in the MGC context, which extends the research on consumer engagement with social media from the context of user-generated content to the MGC.

Keywords Marketer-generated content, Content-generating devices, Consumer engagement, Content features, Social media

Paper type Research paper

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1. Introduction

Because of its persuasiveness, social media has been widely used to foster consumer engagement (Lee *et al.*, 2018; McShane *et al.*, 2021; Pezzuti *et al.*, 2021). Marketer-generated content (MGC) has been regarded as a critical factor that can help firms maintain competitive advantages in volatile markets by enhancing consumer engagement and increasing revenue and consumer retention (Lee *et al.*, 2018; Meire *et al.*, 2019; Weiger *et al.*, 2019). Moreover, marketers invest in MGC on social media to encourage consumer engagement (such as comments, likes or sharing) (Chandrasekaran *et al.*, 2019). By consumer engagement, we mean interactions between consumers and brands through MGC generated via mobile devices or personal computers (PCs) (Meire *et al.*, 2019).

Smartphones' extensive use has dramatically changed individuals' approaches to content generation and communication. People have shifted away from their reliance on PCs and toward mobile devices because of their convenience (Lee *et al.*, 2020). Social media platforms also allow consumers to learn which device has been used to generate social media content since both user-generated content (UGC) and MGC can display such information through icons. Previous research has shown that device types used in generating UGC can affect consumers' perception of and behavior toward UGC (Grewal and Stephen, 2019; Ransbotham *et al.*, 2019). For example, in terms of content features, UGC generated with mobile devices differs from UGC generated via PCs (Zhu *et al.*, 2020). Moreover, consumers perceive UGC generated through mobile devices as more credible than PC-generated UGC (Grewal and Stephen, 2019). However, prior literature has mainly focused on examining the impact of device types on consumer perceptions and behaviors in the UGC context. By contrast, little is known about the MGC context. Specifically, previous research has rarely examined how device types applied in generating MGC affect consumer engagement with MGC. An understanding of how MGC-generating device types (mobile phones versus PCs) affect consumer engagement with MGC could offer new insights into social media marketing.

Apart from device types, MGC content features have been suggested as another crucial factor affecting consumer engagement with MGC (Cruz *et al.*, 2017; McShane *et al.*, 2021). People respond differently to information with different features (Chen *et al.*, 2020; Li *et al.*, 2018; Lin *et al.*, 2020; Zha *et al.*, 2021; Zhang *et al.*, 2019). Marketers could use more specific words in MGC to reinforce the information they want to express through MGC (Han and Lind, 2017; Tausczik and Pennebaker, 2010). Various MGC content features have been argued to promote consumer engagement, such as textual expressions of certainty (Pezzuti *et al.*, 2021), second-person pronouns in a text (Cruz *et al.*, 2017) and emojis in MGC (McShane *et al.*, 2021). Additionally, information that describes a brand's achievements can help consumers understand the brand's value and appealing backstory (Urde and Greyser, 2015). Marketers have also used more social or achievement-based words in MGC on social media to better convey their intended meaning, aiming to foster consumer engagement (Lv *et al.*, 2021).

The literature has shown that consumer engagement can attract more consumers, increase positive electronic word-of-mouth (eWOM) and consumer loyalty and enhance economic performance (Bapna *et al.*, 2018; Chen *et al.*, 2020; Pezzuti *et al.*, 2021; Ray *et al.*, 2014; Zhang *et al.*, 2020a, b). Consumer engagement has even been argued to drive firms' long-term success (Gopalakrishna *et al.*, 2019). It is meaningful to understand whether applying social and achievement content to MGC can foster consumer engagement, which brings benefit to firms. Therefore, an understanding of how social and achievement features of MGC influence consumer engagement with MGC is needed. However, research has seldom investigated whether MGC's social and achievement features can affect consumer engagement with MGC.

According to construal-level theory (CLT) (Trope and Liberman, 2010), psychological distance – defined as a "subjective experience that something is close or far away from the self" – has a bidirectional relationship with individuals' construal levels (Trope and Liberman, 2010, p. 440). On the one hand, psychological distance determines whether individuals construct an event at a high-level construal or a low-level construal (Trope and Liberman, 2010). On the other hand, when events are constructed using high-level construal terms, their psychological distance could be increased; in contrast, psychological distance is closer to events constructed using low-level construal terms (Trope and Liberman, 2010). For instance, people feel closer – both spatially and temporally – to mobile phones than PCs in their daily lives (Melumad and Pham, 2020). Content that expresses social features makes people feel more lifelike, involving a low-level construal (Tausczik and Pennebaker, 2010). Conversely, content that expresses achievement features is more abstract, emphasizing superordinate central features and leading to a high-level construal (Tausczik and Pennebaker, 2010).

Per CLT, MGC with social and achievement features affects consumers' psychological distance in two directions, potentially influencing their interactions with the MGC. Specifically, MGC with social features may promote consumer engagement with the MGC, whereas MGC with achievement features may reduce consumer engagement. Prior research on the congruency effect suggests that matching the psychological distance associated with MGC content features with an appropriate construal level for an MGC-generating device could improve consumer engagement. However, research has seldom explored how such matching affects consumer engagement with MGC from the CLT perspective of psychological distance.

To bridge the research gaps, the current study examines whether matching the psychological distance associated with an MGC-generating device (a mobile phone or PC) with appropriate construal levels for MGC content features can enhance consumer engagement with the MGC. Specifically, we explore how MGC-generating device types (mobile phones versus PCs) and content features (social and achievement features) of MGC influence consumer engagement with the MGC on social media. We also examine these two factors' interaction effects on consumer engagement, based on CLT. We test consumer engagement with MGC empirically with data from Sina Weibo, a popular social media in China. Our data comprise MGC generated by 210 companies from 2018 to 2021, as well as consumer engagement with the MGC from Sina Weibo. Through this approach, our study enriches the literature on consumer engagement on social media by pairing MGC-generating devices with MGC content features from the CLT perspective of psychological distance.

This paper is structured as follows. Section 2 discusses the theoretical background of this study, including MGC, the impact of content-generating devices on consumer perceptions and behaviors and the CLT. We then discuss our proposed research model and hypotheses in Section 3, before presenting the research method in Section 4. Finally, we discuss our research findings and conclude this study by identifying theoretical and practical implications, the limitations of our research and potential avenues for future research.

2. Theoretical background

2.1 Marketer-generated content

MGC refers to "a firm or brand's communication created and shared through online social networks" (Meire *et al.*, 2019, p. 25), and it is also known as firm-generated content (Liang *et al.*, 2020). Marketers can interact with and promote their products or services to consumers through MGC (Hassan and Ariño, 2016). MGC can help consumers better understand a firm, its brand and its products or services (Goh *et al.*, 2013). MGC can include various content types, such as information-focused, emotion-focused, action-inducing or commercial content (Owusu *et al.*, 2016; Tellis *et al.*, 2019). The core criterion for these classifications is MGC's rational appeal (for information content and transactional content) or emotional appeal (for emotional content) (Estrella-Ramón *et al.*, 2019).

Previous studies have found that different MGC content features can affect consumer engagement, for example, sharing, commenting and liking (Weiger *et al.*, 2019; Yousaf *et al.*, 2021). For example, remunerative MGC increases consumers' commenting, and informative content increases consumers' sharing of MGC (Chandrasekaran *et al.*, 2019). Affiliative MGC drives consumer engagement through autonomous motivation, while utilitarian content drives consumer engagement through controlled motivation (Weiger *et al.*, 2019). Some studies have examined the impacts of other MGC features on consumer engagement (McShane *et al.*, 2021; Pezzuti *et al.*, 2021). For instance, when marketers use more certainty-conveying words in MGC, consumers perceive their brand as more powerful and will be more likely to interact with that brand (Pezzuti *et al.*, 2021). Including more emojis in MGC generates more likes and shares among consumers by increasing consumers' perceived playfulness (McShane *et al.*, 2021). Table 1 presents some recent research on how MGC influences consumer engagement.

Psycholinguistics research has argued that language using more social words can convey information about a communicator's willingness to interact, as well as the quality of their interaction; meanwhile, language using more achievement-based words can provide more details about a communicator's accomplishments and initiatives (Huang *et al.*, 2012; Stephan *et al.*, 2010). MGC with more social or achievement words may affect consumer engagement with a brand since consumers process social and achievement-based words differently. Some natural language processing tools (such as Linguistic Inquiry and Word Count or LIWC) have been developed to calculate the proportions of social and achievement words in a text. However, prior research has seldom considered the social and achievement features when investigating the impact of the content features of MGC on consumer engagement (Packard and Berger, 2021). Therefore, an investigation of how social and achievement features of MGC influence consumer engagement is necessary from a content feature perspective.

2.2 Content-generating devices' effects on consumer perceptions and behaviors

Because of mobile technology's incredible convenience, people increasingly access websites and share information using mobile phones (Luo *et al.*, 2021). Compared to nonmobile devices, such as PCs, mobile phones entail fewer temporal and spatial barriers for users (Ransbotham *et al.*, 2019). People can derive more psychological comfort from touching their mobile phones and feel less temporally distant from their mobile devices than PCs (Kim *et al.*, 2020; Melumad and Pham, 2020; Vahedi and Saiphoo, 2018).

Social media content generated on mobile devices has been found to differ from PC-generated content. For example, users who write reviews on mobile phones are less likely to be influenced by prior reviews in comparison with reviews generated through PCs (Li *et al.*, 2021). Moreover, the messages generated on mobile devices are much shorter (Melumad *et al.*, 2019; Ransbotham *et al.*, 2019), use more pictures, provide higher star ratings and require shorter time intervals than those generated through PCs (Zhu *et al.*, 2020). Content generated on mobile phones tends to use more self-disclosure, personal language styles and private language styles than content created on PCs (Melumad and Meyer, 2020). Ransbotham *et al.* (2019) found that online reviews generated via mobile phones tend to include more emotional vocabulary than those via PCs.

Additionally, studies have shown that consumers harbor different perceptions of the content generated with different devices (Grewal and Stephen, 2019). For example, online reviews generated via mobile phones are perceived to have required more writing effort and have higher credibility, leading to higher purchase intentions than reviews generated through PCs (Grewal and Stephen, 2019). However, Ransbotham *et al.* (2019) argued that the perceived value of online reviews generated on mobile phones is lower for consumers than their corresponding perceptions of reviews produced on PCs; moreover, when consumers use

Study	Content feature	Consumer engagement	Main finding
Chandrasekaran *et al.* (2019)	Remunerative and informative content	Commenting, sharing	Remunerative and informative MGC increases consumers' comments and shares, respectively
Koh *et al.* (2021)	The title's language style	Rating	If the language style in an MGC title meets standard expectations for linguistic behaviors in given social and cultural circumstances, the MGC generates better overall ratings from consumers
Liang *et al.* (2020)	Differences in MGC content	Generating reviews	MGC with comprehensive and detailed descriptions about a service and a host increases consumers' review volume
McShane *et al.* (2021)	Emoji	Liking, sharing	MGC with emoji increases consumers' likes and shares
Moran *et al.* (2020)	Interactivity cues and media richness	Engagement	The interactivity cues and media richness included in MGC increase consumer engagement with a brand
Pezzuti *et al.* (2021)	Language style	Engagement	MGC with more certainty words makes a brand more powerful and increases consumer engagement
Vargo (2016)	Informative cues	Engagement	MGC promoting giveaways influences consumer engagement positively, and promotional MGC influences engagement negatively
Weiger *et al.* (2019)	Affiliative content and utilitarian content	Engagement	MGC with affiliative content increases consumer engagement through autonomous motivation, and MGC with utilitarian content increases consumer engagement through controlled motivation
Yang *et al.* (2020)	Promotion depth and breadth	Sharing	MGC expressing a promotion in depth encourages instant sharing but not distant sharing among consumers. Meanwhile, MGC expressing a promotion in breadth reduces instant sharing but increases distant sharing among consumers
Yousaf *et al.* (2021)	Message vividness and orientation	Engagement	MGC with a more vivid message and more interactive or audio-visual content enhances consumer engagement, whereas MGC with a task-based or instrumental orientation leads to low- or medium-level consumer engagement

Table 1.
Recent research on the impact of marketer-generated content features

nonmobile devices to read online reviews, the perceived value of reviews generated through mobile devices declines (März *et al.*, 2017). Mobile devices' convenience reduces the perceived costs and efforts required to generate online reviews (Kim *et al.*, 2020), whereas mobile devices' small screen size also increases the perceived cost of information searching for consumers (Venkatesh *et al.*, 2003).

Table 2 summarizes previous studies that have investigated the impacts of device types on consumer perceptions and behaviors. Most of these studies have concentrated on UGC. Although prior research has investigated user responses to UGC on social media – such as

Study	Dataset	Core variables IV	DV	Main finding
Grewal and Stephen (2019)	Online reviews (UGC)	Device type (mobile vs. nonmobile)	Helpfulness and purchase intentions	Online reviews generated by consumers through mobile devices are perceived to have required more writing effort and have higher credibility, generating greater purchase intentions
Kim *et al.* (2020)	Online review (UGC)	Device type (mobile versus nonmobile)	Content feature differences	The extremity of online reviews generated via mobile devices exceeds the extremity of online reviews generated by nonmobile devices
Lee *et al.* (2020)	Field experiment data	Device type (mobile vs. PC)	Consumer engagement and sales	A recommendation system's impact on consumer engagement is significantly higher for mobile users than for PC users. Although the mobile channel leads to more product sales, the recommendation system and mobile channel have no interaction effects on sales
Li *et al.* (2021)	Online reviews (UGC)	Mobile devices	Review conformity	Temporal distance influences review conformity positively, and mobile devices weaken this positive effect
Mariani *et al.* (2019)	Online review (UGC)	Device type (mobile vs. PC)	Content feature differences	The content features of online reviews generated via mobile devices significantly differ from PC-generated reviews
Melumad and Meyer (2020)	Online reviews (UGC)	Device type (mobile vs. PC)	Enhanced depth of disclosure	Consumers tend to exhibit deeper disclosure when creating online reviews on mobile devices versus PCs
Melumad *et al.* (2019)	UGC	Device type (mobile vs. PC)	Content differences, perceived value	UGC generated with a smartphone is less specific and privileged compared to UGC generated on a PC
Piccoli and Ott (2014)	Online reviews (UGC)	Device type (mobile vs. PC)	Content feature differences, perceived value	Online reviews posted via mobile devices are more timely, shorter, more "to the point" and more negative than reviews posted via PCs
Ransbotham *et al.* (2019)	Online reviews (UGC)	Device type (mobile vs. PC)	Content differences, perceived value	Online reviews generated via mobile devices are more affective, more concrete and less extreme than reviews generated via PCs. Additionally, consumers value mobile reviews less than PC-generated reviews

(*continued*)

Table 2.
Recent research on device types in the social media context

Study	Dataset	Core variables IV	DV	Main finding
Raphaeli *et al.* (2017)	Clickstream data	Device type (mobile vs. PC)	Online browsing behavior	Online browsing sessions through mobile devices are a more task-oriented behavior, and corresponding sessions via PCs are a more exploration-oriented behavior
Söderlund *et al.* (2019)	Experimental data (UGC)	Device type (mobile vs. PC)	Emotional reactions	Responses from consumers via PCs are perceived to reflect more positive emotions and attractiveness than responses via mobile devices with small screens
Zhu *et al.* (2020)	Online reviews (UGC)	Device type (mobile vs. PC)	Content feature differences, perceived value	Online reviews posted via mobile phones include fewer words but more images, as well as higher ratings and shorter time intervals than reviews via PCs

Note(s): "IV" indicates independent variables and "DV" indicates dependent variables

Table 2.

purchasing intentions and browsing behaviors – few studies have explored device types on consumer engagement, especially in the MGC context.

2.3 Construal level theory

CLT explains the relationship between psychological distance and an individual's thinking about an event at an abstract or concrete level (Liberman *et al.*, 2007). CLT posits that people express information at various levels of abstraction, and psychological distance affects how people express and interpret relevant information (Trope and Liberman, 2010). Psychological distance refers to a perceiver's subjective distance from a target object in his/her psychological space (Trope and Liberman, 2003). CLT posits that, when psychological distance increases, individuals tend to use a high-level construal to represent the object; conversely, when this distance decreases, they tend to use a low-level construal (Trope and Liberman, 2003). The relationship between construal levels and psychological distance is bidirectional; when people perceive an object using a high-level construal, they also increase their psychological distance from the object, but when they use a low-level construal, this distance decreases (Darke *et al.*, 2016; Trope and Liberman, 2010). High construal levels comprise abstracts and central features, whereas low construal levels comprise specific descriptions and detailed object features (Trope and Liberman, 2003). According to CLT, psychological distance can be determined by temporal, spatial and social distances (Trope and Liberman, 2010). If an object is present in the distant future in a physically remote place, it is less related to the self and is more likely to be perceived as psychologically distant; conversely, an object in the near future and a physically close place is more related to the self and is less likely to be perceived as psychologically distant (Park *et al.*, 2020).

CLT and psychological distance are commonly used to explain consumers' cognition and behavior. For example, psychological distance has been used to explain consumers' attention to information; when a person's psychological distance from an object is far, they pay more attention to abstract and central information, but when their psychological distance is close, they pay more attention to concrete and detailed information (Kim *et al.*, 2008). People feel temporally and spatially closer to mobile phones than to PCs (Kim *et al.*, 2020). Prior literature has stated that interactions between companies and consumers on social media, as well as companies' responses to consumers on social media, could shorten consumers' psychological distance from companies (Kim and Song, 2019; Xue *et al.*, 2020). However, shortening psychological distance is not always beneficial. For instance, luxury brands' interactions with consumers through social media can reduce consumers' psychological distance but also reduce consumers' perceptions of a product's value and uniqueness (Park *et al.*, 2020).

Additionally, prior research has used CLT to explain various consumer perceptions, preferences, information processing and behaviors by linking construal levels to psychological distance (Adler and Sarstedt, 2021; Chiang *et al.*, 2021; McGowan *et al.*, 2019). For instance, drawing on CLT, McGowan *et al.* (2019) explained how to attenuate the dissociative group effect by applying an experimental approach. Based on CLT, Chiang *et al.* (2021) examined how the system characteristics of interactive augmented-reality technology (e.g. navigation structures, graphical styles and information content) affect consumers' perceived ease of use, usefulness and acceptance of this technology in retail settings. Huang *et al.* (2021) also examined how consumers' construal levels – such as the temporal distance or temporal orientation of promotions – moderate the impacts of emojis' emotional intensity on their purchasing intentions in the social media advertising context.

Therefore, linking construal levels to psychological distance presents a theoretical framework that explains consumers' perceptions and behaviors. Accordingly, in this study, we linked CLT with psychological distance to examine how device types (mobile phones versus PCs) in generating MGC and content features (social and achievement-based content) of MGC influence consumer engagement with MGC and how the interactions between device types and content features affect consumer engagement with MGC.

3. Hypotheses and research model

3.1 Device types and consumer engagement

Mobile devices' convenience has made people rely more on them, granting them a particular psychological position. Compared to PCs, mobile phones are considered more personal. People use PCs more to work, and commonly use mobile phones to exchange messages with friends and family, watch entertaining videos or follow social media updates (Panova and Carbonell, 2018). Mobile phones' active, personal interactions psychologically comfort users and make them feel more secure than PCs (Melumad and Pham, 2020; Vahedi and Saiphoo, 2018). Mobile phones are closely connected to users (Lee *et al.*, 2020). Therefore, mobile phones are less psychologically distant to consumers temporally, spatially and socially.

When reading MGC generated through mobile phones, consumers feel a shorter psychological distance between themselves and the MGC than they do on PCs. Research has found that such reduced psychological distance can increase consumers' trust in a brand (Brynjolfsson and Smith, 2000), their positive attitudes toward a brand (Li and Sung, 2021) and their willingness to interact with communicators (Holmqvist *et al.*, 2015). Therefore, we assume that consumers will be encouraged to engage with MGC – such as by liking, commenting and sharing – by their reduced psychological distance to MGC generated through mobile phones. Accordingly, we hypothesize:

H1. MGC generated via mobile phones leads to more consumer engagement than MGC generated via PCs.

3.2 Content features and consumer engagement

Social is defined as "relating to activities in which you meet and spend time with other people and that happen during the time when you are not working" (Cambridge University Press, 2021a). Prior research based on text analysis has shown that words with social features – such as hello, thanks, acceptance and friends – express social processes, interactions and interpersonal relationships' quality (Tausczik and Pennebaker, 2010). People have extensive, profound experiences and understandings of these social words in their daily lives (Tausczik and Pennebaker, 2010). Research has also found that, when consumers interact with social-oriented content released by marketers, they post more comments on the content online (Daugherty *et al.*, 2008). Therefore, we assume that MGC with more social features shortens consumers' psychological distance from such content, making them more likely to interact with it, such as by liking, commenting and sharing. Accordingly, we suggest:

> *H2.* MGC with social features is positively associated with consumer engagement.

Achievement is defined as "something very good and difficult that you have succeeded in doing" (Cambridge University Press, 2021b). People can describe achievements using specific words such as winning, achieve and ambition (Tausczik and Pennebaker, 2010). Accordingly, companies have employed marketing strategies to demonstrate their brands' power and improve their reputations by disclosing achievements and outstanding performance (Mkumbuzi, 2015; Sarkar and Bhattacharjee, 2017). However, these strategies' effectiveness has been increasingly challenged since consumers can access rich information from different online channels (Budac and Baltador, 2014). Persuading consumers has become increasingly difficult in the information age (Ham, 2017). Consumers avoid content with prominent commercial features on social media (Tellis *et al.*, 2019). Promoting a brand's achievements can be regarded as commercial advertising (Sarkar and Bhattacharjee, 2017). When MGC text includes more achievement content, consumers are more likely to perceive the MGC content as advertising, increasing their avoidance and psychological distance (Zhang *et al.*, 2020a, b). Additionally, expressions of a company's achievements focus on publicity events, which are tedious, boring and ineffectively promote consumer interactions (Tellis *et al.*, 2019). Therefore, we hypothesize:

> *H3.* MGC with achievement features is negatively associated with consumer engagement.

3.3 The interactive effect of content features and device types

The literature has defined information processing fluency as the degree of ease to which people process and assess information that can enhance their perceptions of and behaviors toward this information (Alter and Oppenheimer, 2008; Connors *et al.*, 2021; Lee and Labroo, 2004). For instance, research has found that construal-based mindset congruencies can increase processing fluency and enhance readers' perceptions of messages' persuasiveness (Lee and Aaker, 2004) and their engagement with the messages (Allard and Griffin, 2017). Connors *et al.* (2021) also found that consumers' information processing fluency is enhanced when the psychological distance of a consumer-brand relationship is paired with an appropriate brand-information construal level, such as abstractness or concreteness. Based on the concepts of information processing fluency and the CLT, we assume that pairing an MGC-generating device's psychological distance with an appropriate construal level for that content – such as social features or achievement features – can increase consumer perceptions of the content's information processing fluency, making the MGC persuasive and encouraging consumers to share, like and comment on it.

Specifically, according to the CLT, the "via mobile phone" icon presented in MGC shortens the psychological distance between the MGC and consumers, causing consumers to construct the MGC at a low-level construal. Moreover, MGC with social features usually uses a low-level construal to represent specific information and content that more closely resembles daily language (Tausczik and Pennebaker, 2010). The short psychological distance to mobile-device-generated MGC is paired with the low construal level that features the social content of MGC, potentially enhancing consumers' perceptions of the MGC's information processing fluency. The enhanced fluency makes MGC with social features more persuasive, potentially encouraging consumers to share, like and comment. Therefore, we hypothesize:

H4. When MGC with more social features is generated via mobile phones, it encourages more consumer engagement.

Meanwhile, per CLT, when MGC is generated via PCs, the psychological distance between this content and consumers increases. Thus, consumers construct this type of MGC at a high-level construal. MGC with achievement features usually emphasizes the abstract and central features of events at a high-level construal. PCs' psychological distance in generating MGC is paired with the high construal level that features achievement content in MGC, increasing consumers' perceived fluency in processing this content. The enhanced fluency also makes MGC with achievement features more persuasive, potentially encouraging consumers to share, like and comment. Therefore, we hypothesize:

H5. When MGC with more achievement features is generated via PCs, it encourages more consumer engagement.

3.4 Research model

Drawing on the CLT and psychological distance, as well as the prior literature, we established a research model to investigate how device types in generating MGC and the content features of MGC influence consumer engagement with MGC. MGC's social and achievement features represent how frequently social words and achievement-based words occur in MGC text, and the devices used to generate MGC on social media include mobile phones and PCs. We assume that device types and the social and achievement features affect consumer engagement and device types moderate the impacts of the content features (social features and achievement features) of MGC on consumer engagement. Figure 1 depicts the research model in this study.

4. Method

We empirically tested our research model using the MGC data posted on Sina Weibo (weibo.com) by 210 companies. Notably, Sina Weibo, dubbed the Twitter of China, is a popular social media platform, with 523 million monthly active users (Song *et al.*, 2019). It is one of the

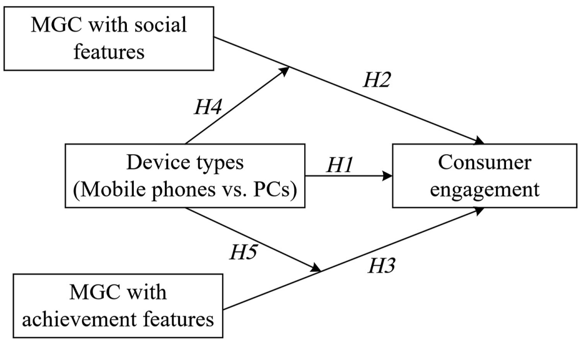

Figure 1.
Research model

leading social media channels for companies to communicate and engage with consumers in China. Therefore, data from Sina Weibo are appropriate for investigating user engagement with MGC on social media.

4.1 Data collection

Our data set included all publicly available MGC records from 210 companies on Sina Weibo between January 2018 and September 2021. The 210 companies we selected are listed on the top-300 ranking companies on Sina Weibo. For each MGC, we collected data regarding content-generating device types, text content and the numbers of likes, comments and shares. We excluded MGC with no device type information and MGC posted via third-party software. Our final sample comprised 126,125 MGC records. Of these records, 19.3% (n = 24,367) are text-only, 79.1% (n = 99,722) include both text and a picture or pictures and 2.7% (n = 3,457) include both text and a video or videos.

4.2 Variables

Words are the basic unit of text content, and specific words' frequency in content can reflect that content's features (Pezzuti *et al.*, 2021). Following prior research, we used the Chinese dictionary of the LIWC software to encode and calculate the proportion of social and achievement-based words in our collected MGC to measure the social and achievement features of each MGC (Pezzuti *et al.*, 2021). LIWC uses natural language processing to classify various categories of words in text content and calculate word frequencies (Tausczik and Pennebaker, 2010). This software has been widely used to assess social media's content features (Grewal and Stephen, 2019; Pezzuti *et al.*, 2021). LIWC contains a total of 80 dictionaries that define and list words such as personal pronouns, auxiliary verbs, affective words, social words and achievement-based words (Huang *et al.*, 2012; Packard and Berger, 2021). For instance, the social dictionary contains 587 Chinese words that describe social processes, social interactions and interpersonal relationship quality in text content (e.g. hello, dating, thanks, family, friends, acceptance and greeting). Meanwhile, the achievement dictionary contains 352 Chinese words that describe success and the process of pursuing success (e.g. leader, ambition, winning, achieve, skillful, success, achievement and expert) (Huang *et al.*, 2012; Packard and Berger, 2021). These specific words' frequency in MGC can reflect what content generators wish to express, constituting MGC's content features. In our final data set, 86.0% (n = 108,491) of MGC records contained at least one word representing social features, and 47.8% (n = 60,320) contained at least one word representing achievement features. And 25,681 MGC records had been generated via mobile phones, whereas 100,444 via PCs.

We set up a dummy variable to indicate the devices used to generate MGC. Mobile phones were coded as *1,* and PCs were coded as *-1*. Following Pezzuti *et al.* (2021), we assessed consumer engagement using the total number of likes, comments and shares for each MGC. Additionally, we included some control variables that have been found to affect consumers' information processing, including word counts of each MGC message, the inclusion of any pictures, the inclusion of any videos, the frequency of affective words and the frequency of personal pronouns (Labrecque *et al.*, 2020; Lee *et al.*, 2020; Ransbotham *et al.*, 2019; Vries *et al.*, 2012). Our model's construct definitions are presented in Table 3.

4.3 Data analysis

We first evaluated the statistical distribution of the data set. The number for consumer engagement (the total number of likes, comments and shares) for each MGC was count data

Variable	Definition	Proxy	Reference
Independent variable			
Device types	The devices individuals use to generate MGC messages on Sina Weibo	−1 = PCs; 1 = Mobile phones	Raphaeli *et al.* (2017)
Social features	The description of social processes, interactions and the quality of interpersonal relationships in the text content of an MGC message	The ratio of social words used in an MGC message compared to the total number of words in that message	Huang *et al.* (2012)
Achievement features	The description of success and the process of pursuing success in the text content of an MGC message	The ratio of achievement-based words used in an MGC message compared to the total number of words in that message	Huang *et al.* (2012)
Dependent variable			
Consumer engagement	The interaction between consumers and MGC	The total number of likes, comments and shares for each MGC record	Pezzuti *et al.* (2021)
Control variable			
Picture	Whether an MGC message contains a picture or pictures	0 = No; 1 = Yes	Lee *et al.* (2020)
Video	Whether an MGC message contains a video or videos	0 = No; 1 = Yes	Lee *et al.* (2020)
Word count	The number of words in the text content of an MGC message	The number of words in each minute recorded for the text content of an MGC message	Fieder *et al.* (2018)
First-person pronouns' frequency	The number of first-person pronoun words in the text content of an MGC message	The ratio of first-person pronouns used in an MGC message compared to the total number of words in that message	Labrecque *et al.* (2020)
Second-person pronouns' frequency	The number of second-person pronoun words in the text content of an MGC message	The ratio of second-person pronouns used in an MGC message compared to the total number of words in that message	Labrecque *et al.* (2020)
Third-person pronouns' frequency	The number of third-person pronoun words in the text content of an MGC message	The ratio of third-person used in an MGC message compared to the total number of words in that message	Labrecque *et al.* (2020)
Affective words' frequency	The number of affective words in the text content of an MGC message	The ratio of affective words used in an MGC message compared to the total number of words in that message	Ransbotham *et al.* (2019)

Table 3.
Variables and measurements

distributed with a positive skew. For example, the number of likes for each MGC ranged from 0 to 5,488,326 (mean = 4586.92; skewness = 44.74; standard deviation = 43794.44; standard error = 0.01); the number of shares per MGC ranged from 0 to 1,092,936 (mean = 2534.62; skewness = 24.49; standard deviation = 35812.71; standard error = 0.01); and the number of comments per MGC ranged from 0 to 549,305 (mean = 543.98; skewness = 43.64; standard deviation = 5444.20; standard error = 0.01), indicating the data set's over-dispersion. Therefore, negative binomial regression was employed in the data analysis since it is suitable for count data that exhibit over-dispersion (Zeileis *et al.*, 2008). The formula for our data analysis is presented below.

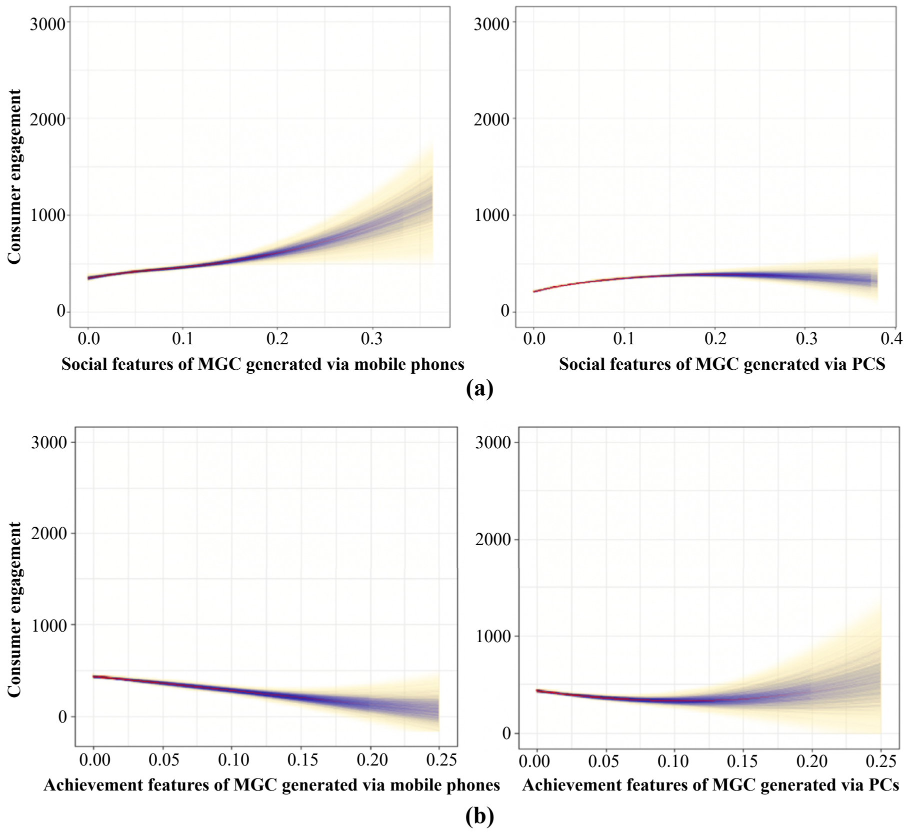

Figure 2. The impacts of content features of MGC generated via different devices on consumer engagement

$$\begin{aligned}\text{Consumer engagement} = {} & \beta_0 + \beta_1(\text{Device types}) + \beta_2(\text{Social features}) \\ & + \beta_3(\text{Achievement features}) \\ & + \beta_4(\text{Device types} \times \text{Social features}) \\ & + \beta_5(\text{Device types} \times \text{Achievement features}) + \beta_6(\text{Picture}) \\ & + \beta_7(\text{Video}) + \beta_8(\text{Word count}) \\ & + \beta_9(\text{First} - \text{person pronouns' frequency}) \\ & + \beta_{10}(\text{Second} - \text{person pronouns' frequency}) \\ & + \beta_{11}(\text{Third} - \text{person pronouns' frequency}) \\ & + \beta_{12}(\text{Affective words' frequency}) + \varepsilon\end{aligned}$$

Figure 2 depicts how different content features of MGC generated on PCs and mobile phones influence consumer engagement. As Figure 2 shows, MGC with (a) social features and (b) achievement features generated on mobile phones and PCs affect consumer engagement differently.

4.4 Results

Our results of negative binomial regression analysis reveal that our model's likelihood ratio test is significant ($\chi^2 = 4536.3$; $p < 0.001$), indicating that negative binomial regression is suitable for this study (Zeileis *et al.*, 2008). We estimated a series of regressions to test our hypotheses (see Table 4). For each model, we checked each variable's variance inflation factor (VIF) value. The greatest VIF value in the models is 1.57, below the vigilance threshold of 5.0 (O'Brien, 2007), indicating that multicollinearity is not a critical issue in this study.

First, we tested the impacts of the independent variables on consumer engagement (see model 1). The test results show that device types significantly affect consumer engagement ($\chi^2 = 2161.8$; $\beta = 0.48$; $p < 0.001$). Compared to PC-generated MGC, mobile-phone-generated MGC receives more consumer engagement, confirming H1.

Models 2 and 4 tested how content features (social and achievement features) of MGC influence consumer engagement with MGC. The results show that MGC's social features have a significant positive impact on consumer engagement ($\chi^2 = 84.29$; $\beta = 0.07$; $p < 0.001$) and that MGC's achievement features have a significant negative impact on consumer engagement ($\chi^2 = 202.17$; $\beta = -0.08$; $p < 0.001$), while the impact of device types on consumer engagement is significant ($\beta = 0.48$ and $p < 0.001$ for Model 2; $\beta = 0.48$ and $p < 0.001$ for Model 4). Therefore, H2 and H3 are supported.

We then tested the interaction effect of device types and content features (social and achievement features) on consumer engagement (see models 3 and 5). Model 3 includes the interaction between device types and social features, based on model 2. The test results show that the interaction between device types and social features has a significant positive impact on consumer engagement ($\chi^2 = 107.53$; $\beta = 0.08$; $p < 0.001$), demonstrating that MGC with more social features generated via mobile phones can encourage more consumer engagement than corresponding content generated via PCs, confirming H4. Model 5 includes the interaction between device types and achievement features, based on model 4. The test results show that the interaction between device types and achievement features has a significant negative impact on consumer engagement ($\chi^2 = -82.62$; $\beta = -0.08$; $p < 0.001$). Therefore, MGC with more achievement features generated via PCs can increase consumer engagement more than corresponding content generated via mobile phones, confirming H5.

Finally, we tested the main impacts of device types, social features, achievement features and their interaction on consumer engagement based on models 6 and 7. Model 6 includes the control variables and all independent variables. The results show that the three independent variables' main effects on consumer engagement are significant ($\chi^2 = 2387.61$; $p < 0.001$). MGC generated via mobile phones receives more consumer engagement than MGC generated via PCs ($\beta = 0.47$; $p < 0.001$). MGC's social features have a significant positive impact on consumer engagement ($\beta = 0.06$; $p < 0.001$), and achievement features exert a significant negative impact on consumer engagement ($\beta = -0.04$; $p < 0.001$), verifying hypotheses H1–H3. Model 7 includes the interaction of device types and social features, as well as the interaction of device types and achievement features, based on model 6. The results confirm the significant interaction effects of device types and content features on consumer engagement ($\chi^2 = 76.30$; $p < 0.001$). The interaction of device types and social features has a significant positive effect on consumer engagement ($\beta = 0.08$; $p < 0.001$). Therefore, MGC with more social features generated via mobile phones can generate more consumer engagement than corresponding content generated via PCs. The interaction of device types and achievement features has a significant negative effect on consumer engagement ($\beta = -0.08$; $p < 0.001$); therefore, MGC with more achievement features generated via PCs can

Table 4. Negative binomial regression results

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	β (se)	*p*	*β (se)*	*p*	*β (se)*	*p*	*β (se)*	*p*	*β (se)*	*p*	*β (se)*	*p*	*β (se)*	*p*
Intercept	8.89 (0.01)	0.000	8.89 (0.01)	0.000	8.89 (0.01)	0.000	8.89 (0.01)	0.000	8.89 (0.01)	0.000	8.89 (0.01)	0.000	8.89 (0.01)	0.000
Picture	0.21 (0.02)	0.000	0.20 (0.02)	0.000	0.19 (0.02)	0.000	0.20 (0.02)	0.000	0.20 (0.02)	0.000	0.20 (0.02)	0.000	0.18 (0.02)	0.000
Video	−1.71 (0.05)	0.000	−1.73 (0.05)	0.000	−1.72 (0.05)	0.000	−1.74 (0.05)	0.000	−1.75 (0.05)	0.000	−1.75 (0.05)	0.000	−1.75 (0.05)	0.000
Word count	0.34 (0.01)	0.000	0.34 (0.01)	0.000	0.33 (0.01)	0.000	0.35 (0.01)	0.000	0.35 (0.01)	0.000	0.35 (0.01)	0.000	0.34 (0.01)	0.000
First-person pronouns' frequency	−0.05 (0.01)	0.000	−0.06 (0.01)	0.000	−0.06 (0.01)	0.000	−0.05 (0.01)	0.000	−0.05 (0.01)	0.000	−0.06 (0.01)	0.000	−0.06 (0.01)	0.000
Second-person pronouns' frequency	−0.14 (0.01)	0.000	−0.17 (0.01)	0.000	−0.17 (0.01)	0.000	−0.15 (0.01)	0.000	−0.15 (0.01)	0.000	−0.17 (0.01)	0.000	−0.17 (0.01)	0.000
Third-person pronouns' frequency	0.14 (0.01)	0.000	0.13 (0.01)	0.000	0.13 (0.01)	0.000	0.15 (0.01)	0.000	0.15 (0.01)	0.000	0.14 (0.01)	0.000	0.13 (0.01)	0.000
Affective words' frequency	−0.05 (0.01)	0.000	−0.06 (0.01)	0.000	−0.07 (0.01)	0.000	−0.03 (0.01)	0.000	−0.02 (0.01)	0.002	−0.03 (0.01)	0.000	−0.03 (0.01)	0.000
Device types (DT) (mobile phone = 1, PC = −1)	*0.48 (0.01)*	*0.000*	*0.48 (0.01)*	*0.000*	*0.48 (0.01)*	*0.000*	*0.48 (0.01)*	*0.000*	*0.48 (0.01)*	*0.000*	*0.47 (0.01)*	*0.000*	*0.45 (0.01)*	*0.000*
Social features (SF)			*0.07 (0.01)*	*0.000*	*0.11 (0.01)*	*0.000*					*0.06 (0.01)*	*0.000*	*0.10 (0.01)*	*0.000*
*DT * SF*					*0.08 (0.01)*	*0.000*							*0.08 (0.01)*	*0.000*
Achievement features (AF)							*−0.08 (0.01)*	*0.000*	*−0.09 (0.01)*	*0.000*	*−0.04 (0.01)*	*0.000*	*−0.08 (0.01)*	*0.000*
*DT * AF*									*−0.08 (0.01)*	*0.000*			*−0.08 (0.01)*	*0.000*
Maximum VIF	1.31		1.48		2.01		1.31		1.52		1.48		1.57	
2*log likelihood	−1994919.91		−1994835.62		−1994728.09		−1994717.74		−1994800.36		−1994694.11		−1994618.41	
Likelihood ratio	2161.80	0.000	84.29	0.000	107.53	0.000	202.17	0.000	−82.62	0.000	2387.61	0.000	76.30	0.000
AIC	1,994,942		1,994,860		1,994,754		1,994,742		1,994,436		1,9947,20		1,994,630	
BIC	1,995,049		1,994,977		1,994,881		1,994,859		1,994,721		1,994,847		1,994,777	

Note(s): "se" refers to the standard error and is shown in parentheses generate more consumer engagement than corresponding content generated via mobile phones, verifying hypotheses H4 and H5.

5. Discussion

This study investigates how MGC-generating devices and MGC content features influence consumer engagement based on panel data comprising MGC records and consumer engagement activities. We found that device types significantly influence consumer engagement with MGC. Specifically, MGC generated via mobile phones leads to more consumer engagement than MGC generated via PCs. Prior literature has indicated that mobile phones are temporally, spatially, and socially closer to consumers than PCs in terms of psychological distance (Kim *et al.*, 2020). Therefore, MGC generated via mobile phones reduces the psychological distance between the MGC and consumers, making the MGC to be more persuasive, which will encourage more consumer engagement than MGC generated via PCs. This finding echoes Grewal and Stephen's (2019) study, which found that mobile-phone-generated UGC on social media attracts more consumer engagement than corresponding PC-generated UGC, though the current study has focused on how device types affect consumer engagement with MGC on social media instead of UGC. Our findings emphasize that device types play an essential role in triggering consumer engagement with MGC on social media.

The current study also found that MGC's social features positively affect consumer engagement, whereas its achievement features negatively affect consumer engagement. Prior literature has argued that content with social features makes people feel more lifelike. Thus, the social features of MGC are close to consumers' daily lives (Tausczik and Pennebaker, 2010), which can shorten the psychological distance between MGC and consumers. The short psychological distance between MGC and consumers triggers consumers' positive perceptions of the MGC, such as credibility and persuasiveness of the MGC, encouraging consumer engagement through likes, shares and comments. On the other hand, consumers perceive MGC promoting achievements as advertising-oriented (Sarkar and Bhattacharjee, 2017), increasing the psychological distance between MGC and consumers. When consumers perceive achievement-based MGC as promotion content, aiming to persuade them to trust a brand or purchase products and services, they are less likely to engage with the MGC by sharing, commenting or liking this content as consumers normally avoid their interaction with the commercial-advertising MGC. Therefore, consumers do not share, comment on or like such MGC. In other words, consumers engage less with this type of MGC.

Moreover, we found significant interaction effects between MGC content features and device types on consumer engagement. Specifically, MGC with more social features generated via mobile phones leads to more consumer engagement than PC-generated MGC, and MGC with more achievement features generated via PCs leads to more consumer engagement than mobile-phone-generated MGC. These findings can be explained by the congruency effect, in which the psychological distance of MGC-generating devices is paired with MGC content features' construal levels. As prior literature has indicated, mobile phones are psychologically closer to consumers than PCs (Kim *et al.*, 2020). Thus, an icon signifying that MGC was generated via a mobile phone shortens the psychological distance between the MGC and consumers, causing consumers to construct this content at a low-level construal. Meanwhile, when MGC is generated via PCs, the psychological distance between this content and consumers increases. Thus, consumers construct this content at a high-level construal (Trope and Liberman, 2010). As we discussed in the previous paragraph, MGC with more social features can also shorten the psychological distance between the MGC and consumers, and this content is constructed at a low-level construal, while MGC with more achievement-based features is constructed at a high-level construal. The pairing of MGC's social features with mobile phones and the pairing of MGC's achievement features with PCs increase consumers' MGC-processing fluency, satisfying their construal-level and content preferences and encouraging consumer engagement. Connors *et al.* (2021) found a similar congruency effect from the construal levels of consumer-brand relationships and appropriate construal levels for brand marketing information on improving consumers' brand evaluations and spending. The current research has demonstrated that appropriately pairing the construal levels of MGC content features and MGC-generating devices can enhance consumer engagement through the congruency effect. These findings also help explain conflicting findings on how mobile devices influence consumer attitudes and behaviors vis-à-vis online reviews (e.g. Ransbotham *et al.*, 2019; Tseng and Wei, 2020; Zhu *et al.*, 2020).

6. Conclusion

6.1 Theoretical implications

This study offers several theoretical contributions to the literature. First, this study contributes to the research on consumer engagement in social media by proposing a congruence perspective in explaining the interaction effects of device types and MGC content features on consumer engagement based on the CLT of psychological distance. Our findings on the interaction effects of device types and MGC content features establish boundary conditions for content marketing's efficacy in consumer engagement across both PC-based and mobile channels. While previous studies have concentrated on the direct effect of device types or content features on consumer responses (Grewal and Stephen, 2019; Pezzuti *et al.*, 2021), the current study has examined the interaction effect of MGC content features and device types on consumer engagement, providing a deeper understanding of how to combine content strategies and technological strategies in order to enhance consumer engagement with MGC by pairing the construal levels of content-generating devices and content features of MGC.

Second, the current work enriches the MGC literature by verifying how the device types used in generating MGC influence consumer engagement with MGC from the CLT perspective of psychological distance. Prior research has focused on UGC when investigating how device types used in generating UGC influence consumer engagement. The current study is, to our knowledge, the first empirical research to investigate the effects of device types on consumer engagement in the MGC context, which extends the understanding of the role of device types on consumer engagement from the UGC literature to the MGC context. This study also provides evidence that the CLT perspective of psychological distance can explain MGC-generating devices' role in triggering consumer engagement behavior toward MGC.

Third, this research contributes to the MGC literature by investigating the impact of MGC content features on consumer engagement. The positive impact of MGC's social features on consumer engagement and the corresponding negative impact of MGC's achievement features indicate that different MGC content features can determine consumers' psychological distance from MGC, potentially leading to different consumer responses to MGC. This work has answered recent calls for more research examining MGC content features and their influence on consumer behavior (Pezzuti *et al.*, 2021).

6.2 Practical implications

Our findings can be translated into practical guidelines to help companies make informed decisions regarding their MGC strategies in social media marketing. First, our findings show that MGC generated via mobile phones generates more consumer engagement than MGC generated by PCs. Since most social media platforms currently label MGC's generating device type, marketers should consider increasing consumer engagement by generating MGC via mobile devices. The data used in this study also show that mobile devices seem underutilized in MGC, generating approximately 20% of MGC applied in this study. This finding suggests that companies should increase their use of mobile devices to generate MGC.

Second, our study shows that the social features of MGC can trigger consumer engagement, but achievement features can reduce consumer engagement. These findings indicate that companies should consider using social features more in their MGC text content in their social media marketing to increase consumer engagement with MGC.

Finally, the findings on the interaction effects between MGC's content features (social and achievement features) and MGC-generating devices offer some practical guidelines for companies on how to combine MGC-generating device types and MGC's content features to enhance consumer engagement with MGC. Specifically, MGC text including more social features should be generated via mobile devices, potentially leading to more consumer engagement. Moreover, MGC containing more achievement features should be generated via PCs, potentially enhancing consumer engagement. Although MGC with more achievement features can reduce consumer engagement due to its increased psychological distance, posting the MGC with more achievement features via PCs will enhance consumer engagement due to the congruency of the construal levels of psychological distance.

6.3 Limitations and future research avenues

This study faces several limitations that future research can resolve. First, previous studies have shown that information affects consumers' responses across various social media platforms differently (Pezzuti *et al.*, 2021). In this study, we focus only on one popular social media platform in China (Sina Weibo), which might limit our findings' generalization to other social media platforms. Therefore, future research could replicate this study across different social media platforms. Second, our research examines only how social and achievement-based content features of MGC and device types in generating MGC affect consumer engagement with MGC. Future research could explore how other MGC content features and device types used in generating MGC influence consumer engagement, as well as their interaction effects. Additionally, future studies could extend the current research to other consumer responses, such as brand attitudes, brand preferences and consumer purchasing intentions. Finally, our study used an established dictionary that equally weighted all words. Future research could consider more granular data analysis approaches to identify the most effective social and achievement-related words in MGC, such as text mining and machine learning.

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