WHOSE AND WHAT CONTENT MATTERS? CONSUMERS' LIKING BEHAVIOR TOWARD ADVERTISEMENTS IN MICROBLOGS

Xiumin Chu
School of Management, Hefei University of Technology
Key Laboratory of Process Optimization and Intelligent Decision Making
No. 193, Tunxi Road, Hefei, Anhui Province, 230009, P.R. China
chuxiumin03@163.com

Yezheng Liu
School of Management, Hefei University of Technology
Key Laboratory of Process Optimization and Intelligent Decision Making
No. 193, Tunxi Road, Hefei, Anhui Province, 230009, P.R. China
liuyezheng@hfut.edu.cn

Xiayu Chen*
School of Management, Hefei University of Technology
Key Laboratory of Process Optimization and Intelligent Decision Making
No. 193, Tunxi Road, Hefei, Anhui Province, 230009, P.R. China
xychen@hfut.edu.cn

Haifeng Ling
School of Management, Hefei University of Technology
Key Laboratory of Process Optimization and Intelligent Decision Making
No. 193, Tunxi Road, Hefei, Anhui Province, 230009, P.R. China
haifling@hfut.edu.cn

ABSTRACT

Drawing on heuristic-systematic model, this study develops a research model to examine how content factors (i.e., persuasive and informative cues) and source factors (i.e., brand popularity and reputation) affect consumers' liking behavior toward advertisements in microblogs, specifically on Weibo. Brand type is regarded as a moderator in the research model, which is empirically evaluated using over 240,000 tweets across approximately 70 auto brands collected from Weibo. Manual coding and machine learning algorithms are integrated to develop a classification model that tags tweets. Results show that content factors (i.e., persuasive and informative cues) and source factors (i.e., brand popularity and reputation) have significant influence on consumers' liking behavior toward advertisement tweets in microblogs. Source factors exert stronger effects on tweet liking than content factors. Particularly, brand popularity is more powerful in increasing the number of likes than brand reputation. In addition, we find that these relationships vary significantly depending on brand type. For functional brands, persuasive cues tend to result in more tweet likes, whereas source factors are more powerful for prestige brands in driving consumers to like their advertisement tweets. Our findings enhance the current understanding of consumers' liking behavior on social media and provide managerial insights for brands seeking to facilitate consumer engagement.

Keywords: Social media; Advertisement; Liking behavior; Heuristic-systematic Model; Source credibility

1. Introduction

The advertisement spending on social media is expected to reach \$28.5 billion in 2020 from \$10.5 billion in 2015 in the United States [Newswire 2016]. According to recent reports from eMarketer [eMarketer 2018b; a], Weibo users will reach 400 million, and its advertising avenue will reach \$2.7 billion in 2020. On the one hand, companies can use social media for marketing and branding. On the other hand, consumers can use social media to connect with their desired brands. A simple quick click (i.e., like) is prevalent on various social media platforms. It reflects consumers'

* Corresponding Author

enjoyment and agreement to the content to a large extent [Lee et al. 2016; Gan 2017; Zell & Moeller 2018]. The number of consumers' "likes" has been regarded as a representation of the advertisement effectiveness of companies on social media [Labrecque & Milne 2012; Rauschnabel et al. 2012; Gan 2017]. Hence, exploring factors that motivate consumers to click "like" on such advertisements is crucial.

Existing literature on consumers' liking behavior has mainly focused on exploring what kinds of content that stimulate consumers to click "like" [De Vries et al. 2012; Luarn et al. 2015; Vargo 2016; Schultz 2017]. Lee et al. [2018] used informative and persuasive messages as two content types of posts on Facebook brand page. Similarly, Luarn et al. [2015] categorized brand posts into remuneration, information, entertainment, and social aspects. Kim et al. [2015] classified social media content into three distinct orientations according to communication orientations. Moreover, Vargo [2016] proposed that brand messages include eight types based on the typology method and further explored which type exerts stronger effect on each engagement behavior. Although various existing research has examined the driving factors of general consumer engagement behaviors (like, comment, and share), relatively few studies have paid attention to consumers' specific liking behavior toward advertisements on social media.

Dual process theory suggests that individuals are often engaged in seeking information validity before judgment formation [Majchrzak & Jarvenpaa 2010]. Extant studies have demonstrated that consumers care more about message source than message content in social networks [Logan et al. 2012; Schulze et al. 2014]. Advertising source that generates tweets exerts a strong potential influence on consumers' behavior [Cotte et al. 2005; Kim et al. 2016]. Moreover, the different effect of advertisements is primarily based on the sources initiating the viral marketing [Kim & Ko 2012]. Although the importance of information source has been demonstrated by existing literature, knowledge about how source characteristics affect consumers' liking behavior toward advertisements remains scant.

Meanwhile, prior research has argued that information recipients' involvement and ability may alter their willingness to elaborate on the information, and thus moderate the likelihood of engaging in arguments quality (i.e., content factors) or peripheral cues (i.e., source characteristics) route [Sussman & Siegal 2003; Bhattacherjee & Sanford 2006; Cheung et al. 2012]. Following this concern, brand type (i.e., functional brand or prestige brand), where functional brands are those for which are understood primarily according to product performance and prestige brands are understood primarily in terms of brand images [Park et al. 1991], is proposed to moderate the influence of content and source factors on consumers' liking behavior. It is because brand type affects consumers' willingness to exert efforts in processing advertisement tweets. However, previous studies have overlooked the moderating role of brand type in consumers' liking behavior toward advertisements.

As discussed above, extant research on consumers' liking behavior mainly focuses on systematic factors (i.e., content), whereas the influence of heuristic factors (i.e., source) has been largely ignored. Therefore, the present study aims to integrate these two types of factors into a comprehensive model, explores the power of tweet content (what) and the characteristics of source (who) in enhancing consumers' liking behavior. In other words, we postulate that "who" says "what" matters. On the basis of the above understanding, we aim to address the following research questions:

(1) How do content factors (persuasive and informative cues) affect consumers' liking behavior toward advertisements in microblogs?

(2) How do source factors (brand popularity and reputation) influence consumers' liking behavior toward advertisements in microblogs?

(3) How and to what extent does brand type (functional brand or prestige brand) moderate the effects of content factors and source factors on consumers' liking behavior?

To answer these questions, this study develops a framework drawing upon the heuristic-systematic model (HSM) and examines how content factors (i.e., persuasive and informative cues) and source factors (i.e., brand popularity and reputation) drive consumers to click "like" on advertisement tweets. Furthermore, we investigate how brand type moderates the proposed relationships. The proposed research model is tested using a total of 247,800 unique tweets of 67 different auto brands from Weibo. Natural language processing (NLP) techniques and machine learning algorithms are combined to process the tweets, train the classification model, and tag the tweets.

2. Research background

2.1. Consumers' liking behavior

"Like" is the lowest level of social media behavior, which requires less amount of cognitive efforts than other behaviors, such as comments and shares [Muntinga et al. 2011; Kim & Yang 2017]. This simple and quick click is ubiquitous and wide spreading in diverse social media platforms. Despite requiring minimal effects, "like" reflects consumers' attention, agreement, and enjoyment, is the amount of consumers' social support [Lee et al. 2016; Gan 2017; Zell & Moeller 2018]. Once a tweet is liked, it may make impressions to a wider audience, not only to the consumer who initially liked the post but also to the friends of his/her friends and so on, thus leading to a powerful viral effect. Scholars have demonstrated that consumers' likes are positively related to brand loyalty, and credible word of mouth [Swani & Milne 2017; Seo et al. 2019]. Accordingly, liking behavior has been used as a measure of advertisement effectiveness [Labrecque & Milne 2012; Rauschnabel et al. 2012; Gan 2017].

Table 1 provides a review of relevant studies on "likes". As it shows, most studies have focused on content and have been conducted on the post/message level, manually or using Amazon Mechanical Turk ("AMT") assigned message or post into several pre-defined categories according to its content in limited datasets from Facebook or Twitter [De Vries et al. 2012; Kim et al. 2015; Vargo 2016; Schultz 2017]. We argue that a tweet may contain multiple elements of diverse categories. Simply asking coders or Turkers to put the tweet into two or more categories is a complex and tough task. Therefore, we attempt to tag tweets on the basis of various cues within their content. Such tagging is a simple binary task. In this study, we attempt to analyze tweets on the content level. By combining manual coding and machine learning algorithms, we also aim to explore how various content factors affect consumers' liking behavior toward advertisements on Weibo.

before judgment formation [Majchrzak & Jarvenpaa 2010]. It has been found that consumers are more concerned about message source than message content in social networks [Logan et al. 2012; Schulze et al. 2014]. Although the critical role of information source has been revealed, the influence of source who initiated the post/message has been overlooked in the existing literature, leaving little understanding about how source characteristics affect consumers' liking behavior. We also incorporate source-related characteristics into our research framework to further understand consumers' formation of "likes".Moreover, as suggested by dual process theory, consumers are always involved in seeking information validity

Table 1: Review of relevant studies on "likes".

Study	Independent variable	Moderator	Dependent variable	Source factor	Measurement	Level of analysis	Dataset size	Platform	Method
[Lee et al. 2018]	Persuasive content, Informative content	Industry	The number of likes and comments	---	AMT + NLP	Content level	106,316 messages from 782 companies	Facebook	Aggregate logistic regression
Schultz [2017]	Post categories	---	The number of likes, comments, and shares	---	Manual assigned	Post level	792 posts from 13 brand pages	Facebook	Ordinary least square (OLS) Regression
Leung et al. [2017]	Message content categories, Message format	Hotel levels (luxury, upscale, middle scale, and economy)	The number of likes, comments, and shares	---	Manual coding	Post level	1,837 messages from 12 hotel brand pages	Facebook	Multivariate analysis of variance (MANOVA)
Vargo [2016]	Tweet typology	---	Like counts, retweet counts	---	AMT	Message level	7,747 tweets of 17 brands	Twitter	Lasso regression
Kim et al. [2015]	Content orientations	---	The number of likes, comments, and shares	---	Manual coding	Post level	1,086 posts of 92 global brands	Facebook	MANOVA
Luarn et al. [2015]	Content type	---	The number of likes, comments, and shares	---	Manual coding	Post level	1,030 posts from 10 brand pages	Facebook	Analysis of variance (ANOVA)
Sabate et al. [2014]	Richness (images, videos, and links)	---	The number of likes and comments	---	Manual processing	Post level	164 posts from a given travel agencies	Facebook	OLS regression
De Vries et al. [2012]	Post categories	---	The number of likes and comments	----	Manual coding	Post level	355 posts of 11 brands	Facebook	OLS regression
This study	Persuasive cues and Informative cues	Brand type (functional and prestige brands)	The number of likes	Brand popularity and Brand reputation	Manual coding + Machine learning algorithms	Content level	247,800 tweets of 67 brands	Weibo	OLS regression

2.2. Heuristic-systematic model

The heuristic-systematic model (HSM) is one of the most permanent theories on information processing in the literature. HSM has been adopted and well validated in contexts such as review helpfulness [Yin et al. 2014; Zhang et al. 2014], end-user information processing [Davis & Tuttle 2013], consumers' judgment to message framing [Meyers-Levy & Maheswaran 2004], and so on.

HSM is a dual process of information processing model, which argues that individuals' judgment forming involves two types of modes requiring different levels of cognitive efforts [Todorov et al. 2002]. Information recipients can use two different information processing modes: systematic or heuristic. According to Todorov et al. [2002], systematic processing mode suggests that consumers may be persuaded if they make high-cognitive efforts on scrutinizing the information. This mode of information processing is information intensive and analytically oriented [Chaiken 1980]. Consumers tend to utilize this mode if they are highly motivated to take great cognitive efforts in processing information [Chen & Chaiken 1999]. Heuristic processing mode indicates that people can also be persuaded when they apply simple and easily acquired decision rules to process information [Chaiken 1989]. This view of persuasion suggests that information recipients can rely on accessible cues (e.g., source characteristics) to process information with little efforts [Chaiken 1980].

HSM provides broad and appropriate explanations of individuals' information processing behavior in the context of online communities [Watts & Zhang 2008]. Hence, we employ this model to analyze consumers' liking behavior on advertisement tweets on microblogging platform. In this study, content-related factors (i.e., informative and persuasive cues) are considered as systematic factors because they are explicit tweet content, which consumers can spend efforts in processing them before making the like decision. We also include source-related factors (i.e., brand popularity and reputation) as heuristic factors. It is because individuals can automatically apply brand popularity and reputation to reach quick evaluation of advertisement tweets. For instance, a brand with high reputation can get a favorable first hearing [Chaudhuri 2002] and will be positively interpreted [Mitra & Golder 2006]. Moreover, we explore how these relationships are contingent on brand type (functional vs. prestige brand) for the reason that brand type affects consumers' willingness to exert efforts in processing advertisement tweets.

2.3. Functional vs. prestige brand

Brands are used for consumers to identify an enterprise's offerings and are influential in delivering functional, emotional, and self-expressive benefits [Aaker 1997], and shaping consumers' beliefs and behaviors [Keller & Lehmann 2006]. Park et al. [1991] considered Rolex and Timex as examples, and proposed two brand concepts, in which a function-oriented brand concept is "understood primarily in terms of brand-unique aspects that are related to product performance" whereas a prestige-oriented brand concept is "understood primarily in terms of consumers' expression of self-concepts or images". Lye et al. [2001] investigated how brand type (prestige or functional brand) affects consumer attitude toward brand extensions. The authors claimed that when individuals evaluate luxury goods, they act on an abstract level, namely, image-related level. However, when individuals assess mass market products, they react on a concrete/product-related level. Following the classification of Park et al. [1991], we classify automotive brands into functional and prestige brands.

3. Research framework

Brands communicate intended information. This communication consists of "who says what, how, to whom, and with what effect" [Triandis 1971]. In our study, brands (i.e., who) persistently release advertisement tweets (i.e., what) on their official Weibo account (i.e., how), consumers who are exposed to the tweets (i.e., whom) then process the advertisement, deciding whether to like the tweets or not (i.e., what effect). In considering all of these, we apply HSM to develop a research framework that incorporates content-related characteristics (informative and persuasive cues) as systematic factors and source-related characteristics (brand popularity and reputation) as heuristic factors to investigate how these factors affect consumers' liking behavior in the microblog. Moreover, we explore how these relationships are moderated by brand type (functional vs. prestige brand).

3.1. The impacts of informative and persuasive cues on likes

It is common to classify advertisements into either informative or persuasive [Santilli 1983]. Informative advertisements shift beliefs about products, whereas persuasive advertisements directly shift preferences. Lee et al. [2018] followed the classification method of Resnik & Stern [1977], wherein informative advertisements are classified based on the number of informative cues. Details about products (e.g., deals, price, and availability) are classified as informative cues. Prior studies formulate informative advertising as a kind of advertisement that informs consumers about price and product [Resnik & Stern 1977; Grossman & Shapiro 1984]. However, related laboratory studies [Armstrong 2010] suggest that advertisements include additional content beyond price. Giveaways are easy way to increase customer engagement on Twitter [YouGov 2019]. Messages that mention corporate and brand names are demonstrated to get more likes [Swani & Milne 2017]. In our study, mentions of brands or products and giveaways alike are categorized into informative cues.

Previous persuasion studies, such as Nan and Faber (2004) and Armstrong (2010), classify persuasive content into three strategies (i.e., ethos, pathos, and logos). Ethos is a form of persuasive advertising, which appeals to consumers through celebrity or struggles to acquire trust or goodwill (e.g., through small talk and banter). Philanthropic content within messages inducing empathy can be considered as a form of persuasion via pathos. Messages that contain remarkable facts can drive consumers to adopt products or catch their attention, this form of persuasion is logos. Studies have also revealed that featuring a celebrity in an advertisement can attract the celebrity's fans, increase brand awareness, and encourage trial [Karniouchina 2011; Chan et al. 2013]. Moreover, the positivity and emotionality of advertising content are positively related to its virality [Berger & Milkman 2012; Heimbach & Hinz 2016]. For example, Berger & Milkman [2012] examined the impact of emotional content on news article sharing. Tucker [2014] explored the effects of advertisement persuasiveness on video sharing. Emotional appeals have been suggested as the most effective factors of advertising effectiveness when advertising message involvement is low [Baker & Lutz 2000]. The effect of Humor in advertising can be enhanced by careful consideration of audience and situation [Weinberger & Gulas 1992], because consumers can quickly adopt humorous materials [Wagner et al. 2017]. Furthermore, it is revealed that humorous content positively affects consumers' attitude toward advertisements and brands [Eisend 2009]. With regard to the mentions of holidays, it has been found that brand messages related to holidays can foster more likes than those do not related to holidays [Vargo 2016]. Taken together, the following hypotheses are developed:

H1: Persuasive cues are positively related to consumers' liking behavior.

H2: Informative cues are positively related to consumers' liking behavior.

3.2. The impacts of brand popularity and reputation on likes

Scholars suggest that heuristic information processing can be activated or accessed from memory and situational cues [Petty & Cacioppo 2012]. The introduction of brand popularity and brand reputation can be understood using associative network memory theory [Keller 1993]. When consumers are exposed to an advertisement tweet initiated by a brand, the relevant memory nodes in consumers' brain are activated, resulting in a retrieval of brand associations [Morrin 1999]. Brand awareness, familiarity, and popularity are viewed as components of brand associations in brand equity studies [Blackston 1995; Keller et al. 2011]. Previous research has claimed that features of information creators (e.g., reputation) and familiarity to information receivers influence receivers' perception of information credibility [Hovland et al. 1953]. Information from creators with many positive features appears to be more persuasive than that from creators with few positive features because information receivers likely trust the former [Eagly & Chaiken 1993].

Brand popularity is the extent to which brands have been widely sought after and purchased by the population at large [Kim & Chung 1997]. Popular brands tend to obtain favorable evaluations. Popularity provides customer values by enhancing customers' confidence when they evaluate products whose features are not easily compared with alternatives (e.g., automobiles). Brand popularity provides firm values by enhancing the efficiency and effectiveness of marketing programs, brand extensions, and so on [Koo Kim 1995]. It can reduce consumers' uncertainty by selecting popular brands [Magnini et al. 2013]. Popular brands are trustworthy, thus consumers' evaluations are affected by brand popularity [Kim & Min 2014; Whang et al. 2015]. This positive impact on consumers' behavior can be explained by social norms [Kim & Min 2016]. Steyn et al. [2010] indicated that advertisements from popular groups score higher on the overall likability than those from unpopular groups due to the psychology of social impacts and normative influences. Consumers are influenced by a message source, and they tend to retweet messages from the dominate source (which has many followers) [Geva et al. 2019]. When a brand is popular, consumers assume a certain level of trust and confidence in the brand, thus reducing their uncertainty level [Dean 1999]. Hence, when brand popularity is used as a heuristic cue in advertising, many favorable assessments may be stimulated. Advertisement tweets created by popular brands can relatively obtain more likes in microblogs.

Brand reputation is conceptualized as "backward-looking asset with forward-looking benefits, which consumers ascribe to a brand, based on their previous experience and brand's visibility in the market" [Chaudhuri 2002]. It is consumers' expectations when they encounter a brand they have already purchased or consumed in the past. At a certain level, brand reputation reflects brand ability to deliver its promise. Some scholars have pointed out that reputation signals social validation and credibility [Cialdini 2001]. Brands or companies can benefit from brand reputation, studies have demonstrated that reputed brands/companies are expected to possess higher consumer trust [Sichtmann 2007; Walsh et al. 2009]. Consumers can utilize brand reputation to deal with uncertainty when making decisions [Baek et al. 2010; Wang et al. 2016]. Brand reputation also affects consumers' evaluation toward advertisements. Several studies show that brands with high reputation are likely to receive a favorable first hearing and their advertisements can produce a greater impact [Chaudhuri 2002] and be deduced in a more positive manner [Mitra & Golder 2006]. Moreover, brands with high reputation probably engender higher levels of positive consumer engagement behavior [Walsh et al. 2009]. Hence, in our research context, we assume that advertisement tweets from brands with high reputation are more attractive to consumers and are more likely to be evaluated favorably. The following hypotheses are proposed:

H3: Brand popularity is positively related to consumers' liking behavior.

H4: Brand reputation is positively related to consumers' liking behavior.

3.3. Content factors, source factors and likes

The effect of heuristic factors tends to be greater in low involvement condition [Wilson & Sherrell 1993]. Clicking the like button on social media involves least cognitive efforts because it is the lowest level of consumer–brand interactions [Muntinga et al. 2011; Kim & Yang 2017]. In such a scenario, consumers exposed to advertisement tweets may not be motivated to process advertisement contents elaborately and tend to rely on heuristic factors. In this case, advertisement sources are expected to be more critical factors in determining consumers' subsequent behavior. Empirical studies have demonstrated that consumers are more aware about message source than message content in social networks [Logan et al. 2012; Schulze et al. 2014]. Thus, we proposed the following hypothesis:

H5: Source-related factors exert greater impacts on consumers' liking behavior toward advertisement messages than content-related factors.

3.4. The moderating role of brand type

Interactions between brand type (functional vs. prestige brand) and advertisement content (persuasive and informative cues) may exist because brand type affects consumers' willingness and efforts exerted to process advertisement tweets. Functional brand concept is conceptualized as "understood primarily in terms of brand-unique aspects that are related to product performance" whereas prestige brand concept is "understood primarily in terms of consumers' expression of self-concepts or images" [Park et al. 1991]. For example, tweets from Mercedes (a prestige brand) are likely evaluated by brand image. Functional brands, such as Chery, do not focus on brand image, but on product performance. With the popularity of social media platforms, such as Weibo, consumers tend to use brands to construct their self, and brands are "consumed" through interactions. Consumers utilize brands to mold their impressions on others by interacting with brands [Hollenbeck & Kaikati 2012]. Prestige brands, owning to their own brand image, fuel consumers' self-concept [Hanzaee & Taghipourian 2012]. The predominance of these brands possibly reduces the assumed positive influence of tweets content factors on consumers' liking behavior. The reason is that when consumers make a "like" decision, brands itself play a dominant role. Consumers may unlikely exert great efforts to process tweets, thus the strength of content factors on driving consumers to click "like" is diminished. On the contrary, the content factors of functional brands' tweets can play more important roles in persuading consumers to like the tweets. Therefore, we hypothesize that:

H6: Brand type negatively moderates the effect of persuasive cues on consumers' liking behavior. For functional brands, persuasive cues in advertisement tweets have stronger impacts on the liking behavior.

H7: Brand type negatively moderates the effect of informative cues on consumers' liking behavior. For functional brands, informative cues in advertisement tweets have stronger impacts on the liking behavior.

Brand popularity and reputation both signal information validity at certain level. However, they may not be of equal importance for all conditions and may vary depending on brand type consumers exposed to. Brand popularity signals the extent to which consumers seek after a brand [Kim & Chung 1997]. For prestige brands, brand popularity may suggest that many people attempt to acquire self-expression through it. According to bandwagon effect, consumers tend to interact with this type of brands to construct their selves, so consumers exposed to advertisements from prestige brands are probable to be engaged. However, such advertisements can also negatively affect brand evaluation owning to congestion and loss of exclusivity [Hellofs & Jacobson 1999]. Prestige brand image may be lost because of wide-spread popularity. Nevertheless, prestige brands (such as Mercedes and BMW) are often premium priced and used to convey wealth or status [Verhoef et al. 2007]. Brand popularity hardly leads to congestion and loss of exclusivity. Thus, the influence of prestige brands' popularity on consumers' liking behavior is enhanced. By contrast, functional brands' popularity indicates that these brands are sought after and purchased by consumers because brand popularity serves as a signal of product quality. Product quality is critical for functional brands. However, cars are complex products with many attributes, whose quality may not be easily accessible without extensive information search. When consumers evaluate quality, they tend to reply more on intrinsic cues and less on extrinsic cues (e.g., brand popularity) [Petty et al. 1983]. The power of functional brands' popularity in enhancing consumers' liking behavior may be weaker. Brand reputation reflects brands' ability to deliver their promise. It is of critical importance both for prestige and functional brands. However, prestige concepts are more widely known and salient than functional concepts [Lye et al. 2001]. Thus, the influence of brand reputation on the number of likes is more enhanced for prestige brands than for functional brands. Given all that, we formulate that:

H8: Brand type positively moderates the effects of brand popularity on consumers' liking behavior. For prestige brands, brand popularity has a stronger impact on the liking behavior.

H9: Brand type positively moderates the effects of brand reputation on consumers' liking behavior. For prestige *brands, brand reputation has a stronger impact on the liking behavior.*

3.5. Control variables

Prior studies on consumers' liking behavior have suggested that systematic cues—different aspects of post/tweet content, tweet/post length, and whether the posts/tweets contain photos, videos, or links—affecting consumers' liking behavior [De Vries et al. 2012; Vargo 2016; Schultz 2017; Lee et al. 2018]. Photos, videos, and links are considered because they enhance the richness and interactivity of posts/messages, and thus exert impacts on consumers' behavior (like, comment, and share) [De Vries et al. 2012; Sabate et al. 2014; Schultz 2017; Lee et al. 2018]. Likewise, the grade of brand account, which is determined by the accumulated experience value of users, is included in our model. Such a grade reflects brands' communication intensity, indicating how active brands are. The more active brands are, the more likes their posts can obtain [Kumar et al. 2016; Davis et al. 2019]. Moreover, a large number of fans may increase the likelihood of obtaining likes [Sabate et al. 2014; Schultz 2017]. Thus, these variables are introduced as control variables in the present study.

The research framework for the factors influencing consumers' liking behavior is illustrated in Figure 1.

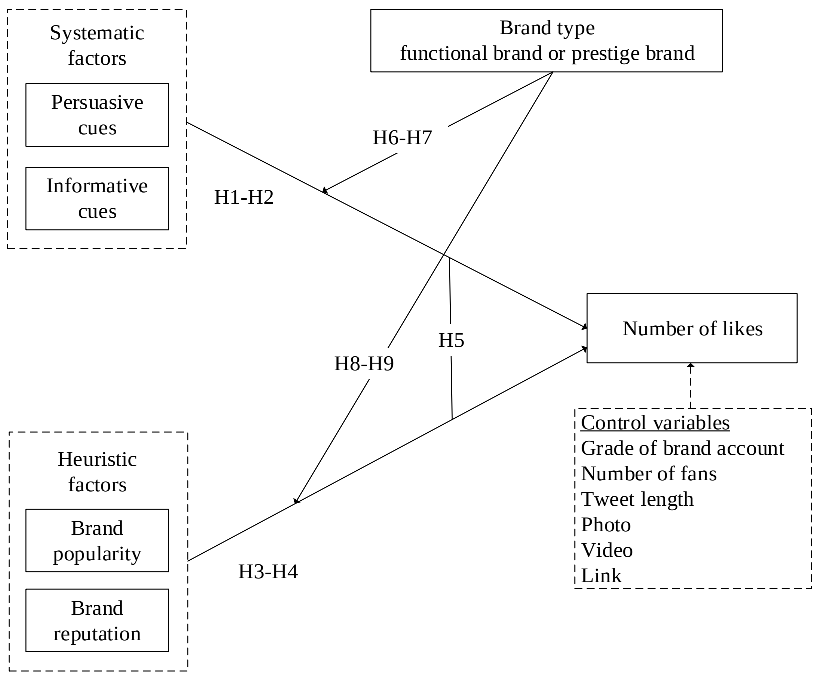

Figure 1: Research framework

4. Research method

4.1. Data collection

The research context of this study is Weibo, which is the most popular microblogging platform in China. Compared with other social media, microblogs possess three basic traits: brevity, real time, and voluntary relationship [Yin et al. 2018]. Brevity refers to the limit of tweet length (140 characters). Real time implies that microblogs are available anytime and anywhere, allowing consumers to frequently share and obtain information. Voluntary relationship indicates the asymmetric and unidirectional following and followed connections. These traits make microblogs effective platform for advertisements [MarketingToChina 2017].

This study aims to examine the factors affecting consumers to click "like" toward advertisements in microblogs. We employ Weibo API to collect available data regarding the automotive industry from Weibo.com. This industry is appropriate for studying the communication strategies of different brand types because cars are complex products, wherein consumers choose a car brand for different reasons (e.g., prestige, exclusivity, or relative functional characteristics) [Kirmani et al. 1999].

First, we gather available automotive brands together by referring to Autohome[1], a well-known automotive website with the largest global traffic. Second, we search for different brand names in Weibo. The resulting list is

[1] https://www.autohome.com.cn

filtered with two principles: (1) The brand account must be verified by Weibo platform, and (2) The account should be active during the observation period. The final dataset consists of 247,800 tweets of 67 different brands gathered from January 2017 to May 2018. Figure 2 gives the sample advertisement tweets on Weibo. The raised thumb at the lower right represents the number of likes that the advertisement tweets have acquired.

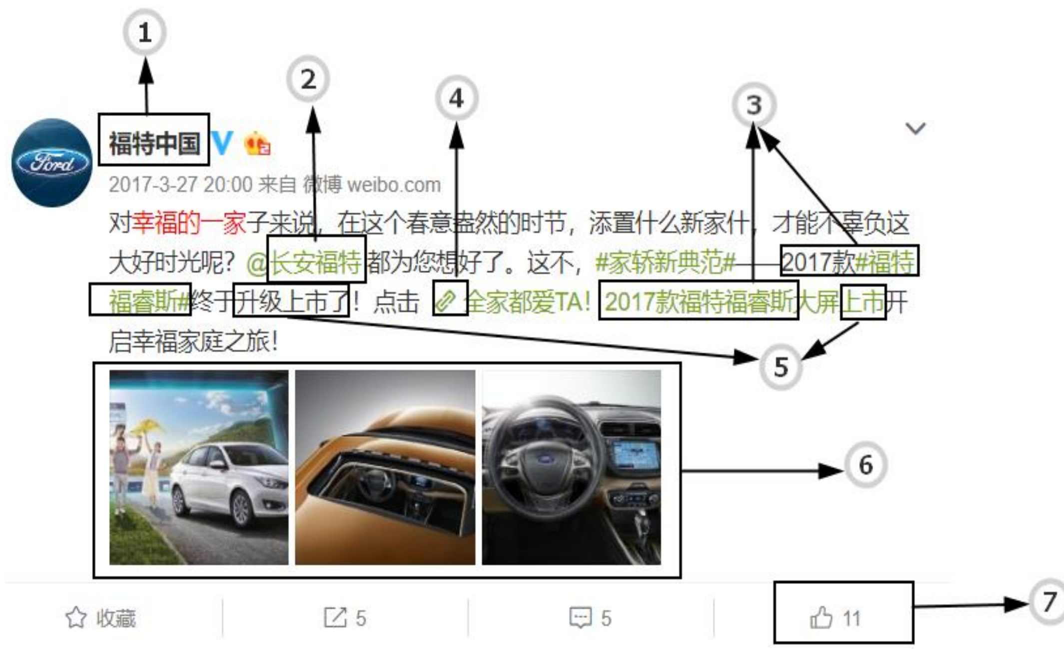

Figure 2: An advertisement tweet from Weibo

Notes: 1. Tweet Source; 2. Brand name; 3. Product name; 4. Link; 5. Remarkable fact (come into the market); 6. Photos; 7. The number of likes. Among of these 2 and 3 are informative cues, 5 is persuasive cue, 4 and 6 are controlled in the present study, 7 is the dependent variable.

4.2. Variables and measurements

The independent variable is the aggregated number of likes that each tweet obtains during the observation period. The explanatory variables are systematic (persuasive and informative cues) and heuristic factors (brand popularity and reputation). Persuasive and informative cues are measured by the number of corresponding content cues, which are calculated by our developed classification model that combines manual coding and machine learning algorithms. The details are stated in the latter classification model of tweets Section. Brand popularity is constructed using the Baidu index[2] which summarizes the volume of Baidu searches for a specific brand in a specific time. Given the period in which brand is active, brand popularity is calculated from January 2017 to May 2018. Brand reputation is measured by a three-item scale developed by Chaudhuri [2002], wherein a total of 32 MBA students are invited as respondents. Brand type is manually coded, treating it as a binary variable, where 0 is assigned for functional brands, and 1 is assigned for prestige brands. Table 2 gives the detailed descriptions and measurements of these variables including control variables.

[2] http://index.baidu.com/

Table 2: Variables and measurements

ID	Variables	Description	Codification and measurements
Control variables			
1	Logfans	Number of users that follow the brand	Numerical≥0, transformed applying natural logarithm function
2	Grade	The grade level of the brand Weibo account	Numerical≥0
3	Tweet length	The number of words	Numerical≥0
4	Photo	Presence of photo in tweet	Yes 1, no 0
5	Video	Existence of video in tweet	Yes 1, no 0
6	Link	Presence of link in tweet	Yes 1, no 0
Independent variables			
7	Persuasive cues	The number of persuasive cues existing in tweet	Manual coding +machine learning algorithms
8	Informative cues	The number of informative cues presented in tweet	Manual coding+ machine learning algorithms
9	Brand popularity	The extent to which a brand has been widely sought	Numerical≥0, search index of each brand on Baidu.com as the proxy for brand popularity, transformed applying natural logarithm function
10	Brand reputation	Consumers' expectations about future encounters with the brand	Three items from [Chaudhuri 2002]
Moderator			
11	Brand type	Functional brand or prestige brand	Functional brand 0 Prestige brand 1
Dependent variables			
12	The number of likes	The accumulative amount of likes the tweet has got	Numerical≥0

4.3. Classification model of tweets

4.3.1. Manual coding for content cues

In this part we describe our manual coding procedures of tweet content cues. Table 3 is the coding manual guiding coders' operation. These binary classification tasks assigned to coders are fairly simple, rather than the complex task which asks coders to classify a whole message into two or more categories. Three postgraduates on relevant research area are invited to tag the samples from twelve brands. The average Cronbach's Alpha of our 1448 tagged sample is 0.80 with a median of 0.75, which is above the acceptable thresholds of 0.7 [Fornell & Larcker 1981]. These content-coding tweets are utilized as training samples in training the classification model in the next stage.

Table 3: Coding manual for content cues

Content cues	Descriptions	Manipulations
Persuasive cues	Mention remarkable fact	Yes 1, no 0
	Present any type of emotion (emotional appeal)	Yes 1, no 0
	Contain emoticon or net slang	Yes 1, no 0
	Mention holidays	Yes 1, no 0
	Use celebrity	Yes 1, no 0
	Humor used	Yes 1, no 0
	Philanthropic or activist related	Yes 1, no 0
	Contain small talk other than product or brand business	Yes 1, no 0
Informative cues	Mention a brand or organization name	Yes 1, no 0
	Mention specific product	Yes 1, no 0
	Offer any type of discounts or freebies, sweepstakes	Yes 1, no 0
	Compare price or makes price match guarantee	Yes 1, no 0
	Contain product price	Yes 1, no 0
	Contain targeted audience	Yes 1, no 0
	Contain information on product availability (e.g., stock or release date)	Yes 1, no 0
	Contain information on where to obtain product	Yes 1, no 0

4.3.2. Training classifier

NLP techniques are used to process and understand human language by computer programming, and have been widely used in recent study due to the considerable available text data online [Goh et al. 2013; Li & Xie 2020]. Our NLP methods are large-scale and multi-step methods, which automatically extract content cues from textual data. Four supervised learning algorithms (logistic regression with L1 regularization and L2 regularization, Naïve Bayes, support vector machine) are combined to label textual data using ensemble methods due to the fact that ensemble learning can tradeoff variance and bias, and finally achieve better classification performance [Rokach 2010; Sun et al. 2015]. We choose these four algorithms because of the following reasons: Logistic regression with L1 regularization considers the number of attributes, whereas Logistic regression with L2 regularization addresses the multicollinearity of problem to prevent over-fitting and improve the generalization. Naive Bayes is a classifier based on Bayes theorem and considers whether features exist or not, and it works better and requires relatively fewer training samples than logistic regression. Support vector machine algorithm in machine learning performs well for high dimensional tasks. To achieve our goal, the coded samples are employed as the training set. Detailed procedures are illustrated in the steps below. Figure 3 demonstrates these processes.

Step 1, data pre-processing. The raw data of 1,448 tweets as training samples are broken into basic blocks, employing stop-word removal (punctuation marks and low information words are removed), word segmentation (breaking sentences into words and phrases), and part-of-speech tagging (determining the part-of-speech of words). In this step, the input is the sentence, and the output is a set of words of semantic values. An NLP framework of Python is implemented in this step.

Step 2, feature selection. To train the classification model, we extract sentence-level attributes and sentence-structure traits to identify tweet content cues. These features include TF-IDF (the term frequency and inverse document frequency), ratio of part-of-speech, bigram, bag of words, the rule of whether particular keywords exist, tweet style (number of characters, words, sentences; average ratio of characters, words, and sentences per tweet), and punctuation marks. Table 4 lists these features and gives their descriptions. These extracted features are regarded as x-variables, the corresponding y-variables are generated by coders in the manual coding Section.

Step 3, classification model training. We train the classification model by using diverse classifiers, namely, logistic regression with L1 and L2 regularization, Naive Bayes, and support vector machine (SVM) with different regulations and kernels.

Step 4, ensemble learning. To attain the classification model, we utilize ensemble methods to combine outcomes from the above classifiers because ensemble learning can reduce variance or bias and achieve better classification performance [Bennett 2006]. By combining these methods, we can develop a better classification model.

Step 5, performance evaluation. The performance of the classification model is evaluated by three measures: precision, accuracy, and recall using a 10-fold cross validation.

Steps 2–5 are repeated until the desired performance is achieved.

Table 5 shows the performance of our final classifier.

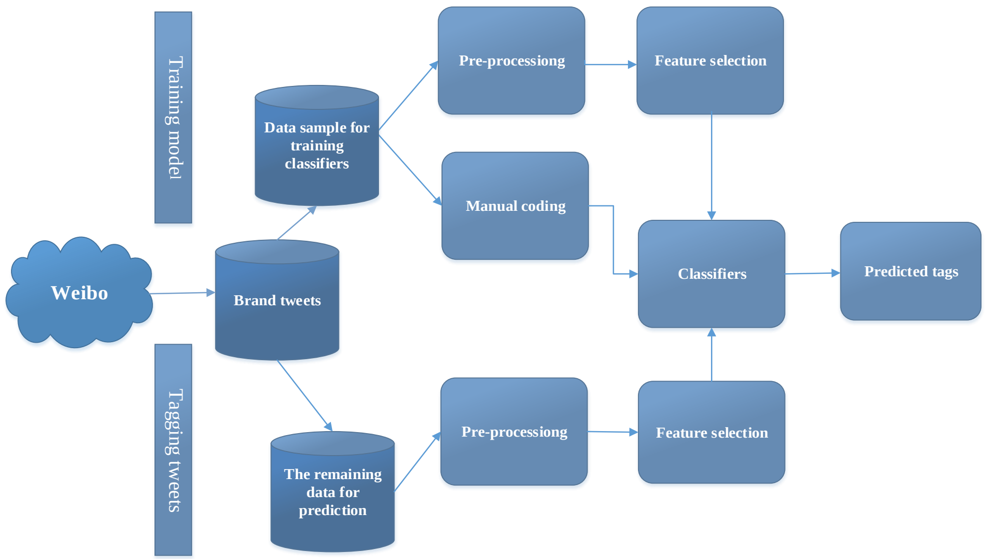

Figure 3: Diagram of training and classification procedure

Table 4: Tweets attributes used for training the classification model

Rules and features	Description
Bag of words	All the words and the frequency of each in a tweet.
Ratio of part-of-speech	The ratio of noun, verb, adj in each tweet.
TF-IDF	Weights each word in tweet using TF-IDF.
Specific keywords	Use dictionaries for different content cues, for example, brand and product lists can be collected and utilized for identification.
Tweet stylish	Number of characters, words, sentences, average ratio of characters, words and sentences per tweet.
Punctuation marks	The frequency of different punctuation marks, e.g., exclamation and question mark.

4.3.3. Tagging new tweets using final classifier

For each new tweet, Steps 1 and 2 are repeated. Subsequently, the ultimate classification model developed above is used to predict whether a particular content cue exists in the tweet.

Table 5: The performance of final classifier

Cues	Precision	Accuracy	Recall
Remarkable fact	0.902	0.902	1
Emotional appeal	0.955	0.955	1
Contains emoticon or net slang	0.960	0.961	1
Mention holidays	0.910	0.909	1
Use celebrity	0.940	0.937	0.996
Humor used	0.990	0.990	1
Philanthropic or activist message	0.972	0.972	1
Small talk	0.814	0.801	0.883
Mention a brand	0.781	0.798	0.576
Mention specific product	0.818	0.808	0.879
Offer any type of discounts or freebies, sweepstakes	0.957	0.955	0.996
Compare price or makes price match guarantee	0.997	0.997	1
Contain product price	0.993	0.993	1
Contain targeted audience	0.977	0.975	1
Product availability	0.990	0.990	1
Contains information on where to obtain product	1	1	1

5. Data description and empirical analysis

5.1. Data description statistics

To measure the impact of advertisement tweet content on liking behavior, two composite summary variables (i.e., persuasive and informative cues) are obtained by adding up corresponding cues, as presented in Table 3. To make it clear, the persuasive cues are the summary of mention remarkable fact, emoticon or net slang, mention holidays, celebrity usage, humor used, philanthropic or activity related and small talk. So persuasive cues range from 0 to 8. Similarly, informative cues are comprised of mentions of brand or product, offerings of discounts or freebies, price comparing, contain product price, targeted audience, product availability and information on where to obtain, and thus are on a scale of 0 to 8. Table 6 presents the statistic description of all samples. On average, prestige brands accumulate more likes than functional brands. Tweets from prestige brands contain more informative cues and prestige brand possess greater popularity. Table 7 reports the correlation of relevant variables. The maximum absolute value of correlation coefficients is 0.602, meeting the critical threshold of 0.7 [Gnyawali et al. 2010].

Table 6: Statistic description of all samples

Variables	All samples (N=247,800)				Prestige brand (N=43,062)				Functional brand (N=204,738)			
	mean	s.d.	min	max	mean	s.d.	min	max	mean	s.d.	min	max
Loglikes	1.81	1.44	0	11.7	2.90	1.53	0	11.49	1.57	1.31	0	11.67
Persuasive cues	1.57	1.75	0	8	1.56	1.96	0	8	1.57	1.70	0	8
Informative cues	1.78	1.84	0	8	2.17	1.90	0	8	1.70	1.82	0	8
Brand popularity	8.53	1.02	5.59	10.29	9.62	0.38	8.54	10.18	8.30	0.96	5.59	10.29
Brand reputation	3.98	0.77	2	6	5.51	0.73	4.3	6	4.87	0.73	3.33	6
Tweet length	41.77	22.79	3	78.75	51.81	26.18	3	77	31.42	29.54	3	78.46
Photo	0.78	0.41	0	1	0.78	0.41	0	1	0.77	0.42	0	1
Video	0.03	0.17	0	1	0.04	0.21	0	1	0.03	0.17	0	1
Link	0.09	0.29	0	1	0.10	0.30	0	1	0.09	0.28	0	1
Logfans	12.80	1.27	5.64	14.77	13.23	0.89	11.70	14.42	12.71	1.32	5.64	14.77
Grade	36.38	5.57	9	46	36.83	3.31	31	43	36.28	5.94	9	46

Note: s.d. = standard deviation

Table 7: The correlations of relevant variables

Variables	1	2	3	4	5	6	7	8	9	10	11
1. loglikes	1.000										
2.Persuasive cues	.052*	1.000									
3.Informative cues	.187***	-.457***	1.000								
4.Brand popularity	.391***	-.094***	.018	1.000							
5.Brand reputation	.490***	-.073***	.103***	.362***	1.000						
6.Tweet length	.095***	-.098***	.379***	.030	.210***	1.000					
7. Photo	.170***	-.039	.061**	.034	.158***	.105***	1.000				
8. Video	.013	-.111***	.141***	.035	-.117***	.051*	-.602***	1.000			
9. Link	-.198***	-.021	-.015	-.122***	-.447***	-.216***	-.084***	.110***	1.000		
10. Logfans	.312***	-.135***	.144***	.491***	.016	.081***	.128***	.021	-.231***	1.000	
11. Grade	.170***	-.078***	.350***	-.087***	-.013	.139***	-.072***	.036	.160***	.009	1.000

Notes: * p<0.1,** p<0.05, *** p<0.01

5.2. Empirical model

To test the proposed research model, this study employs a regression approach to estimate the influence of proposed factors on consumers' liking behavior toward advertisement tweets. Our dependent variable (the number of likes) is a count variable with a Poisson distribution. Consistent with previous research [De Vries et al. 2012; Sabate et al. 2014; Schultz 2017], the dependent variable is transformed by the natural logarithm. Before estimating, we also obtain the variance inflation factor (VIF), which suggests that multiple collinearity is not an issue to run regression (see Table 8). Related variables are also centered before creating the interaction items. Our model can be formulated as below:

$$\ln(likes) = \beta_0 + \sum_{i=1}^{5} \beta_i \times \begin{pmatrix} pecues \\ incues \\ bpop \\ brep \\ btyp \end{pmatrix} + \sum_{j=6}^{9} \beta_j \times btyp \times \begin{pmatrix} pecues \\ incues \\ bpop \\ brep \end{pmatrix} + \sum_{r=10}^{15} \beta_r \begin{pmatrix} grade \\ numfans \\ twlen \\ photo \\ video \\ link \end{pmatrix} + \varepsilon$$

where *likes* is the number of likes the tweet gets; *pecues* refers to the number of persuasive cues in each tweet; *incues* refers to the number of informative cues in each tweet; *bpop* is brand popularity; *brep* is brand reputation; *btype* represents brand type; grade is the grade of brand account on Weibo; *numfans* is the number of followers for the brand; *twlen* is the number of words of each tweet; photo, video and link , dummy variables for each tweet which indicate the presence of photo, video and link; ε is the error term for the like model.

Table 8: The multiple collinearity check (variance inflation factor)

Variables	**VIF**	**1/VIF**
Photo	1.80	0.555
Video	1.77	0.564
Brand popularity	1.75	0.570
Informative cues	1.71	0.586
Brand reputation	1.70	0.588
Log fans	1.68	0.597
Link	1.54	0.651
Persuasive cues	1.31	0.762
Tweet length	1.27	0.789
Grade	1.24	0.809

5.3. Empirical results

Hierarchical regression method is employed, in which Model 1 explores the independent variables on the liking behavior, adding interaction items into the model, Model 2 investigates the moderating role of brand type. Table 9 presents the results.

As shown in Table 9, the model explains 28.84% of the variance in the number of likes. H1, which proposes that persuasive cues positively affect consumers' liking behavior, is supported ($\beta = 0.024$, $p < 0.000$). H2, which states that informative cues in tweets positively affect consumers' liking behavior, is not supported ($\beta = -0.046$, $p < 0.000$). Besides, the comparisons between persuasive cues and informative cues confirm that persuasive cues have a stronger impact on the number of likes than informative cues ($t=0.334$, $p<0.01$). Source factors, brand popularity, and brand reputation both have positive impacts on the liking behavior, the findings are consistent with H3 and H4. Hence, H3 and H4 are supported ($\beta = 0.514$, $p < 0.000$; $\beta = 0.180$, $p < 0.000$). In addition to these, our comparison results indicate that brand popularity exerts a stronger influence on consumers' liking behavior than brand reputation ($t=0.071$, $p<0.01$). Besides, brand type is positively related to the number of likes ($\beta = 0.190$, $p < 0.000$). H5 claims that source-related factors exert greater impacts on the number of likes than tweet content factors. The comparison results between content factors and source factors are all negative and significant. Therefore, H5 is supported. Table 10 lists the testing results of the coefficients comparisons. With all the results above, we can sort the factors according to their power in driving consumers' liking behavior as follows: brand popularity, brand reputation, persuasive cues, and lastly informative cues.

Table 9: The results of hierarchical regression

Variables	Model 1	Model 2
Control variables		
Tweet length	.001***	.001***
Photo	.062***	.051***
Video	.759***	.762***
Link	-.354***	-.362***
Log fans	.151***	.303***
Grade	.008***	.002***
Main effects		
Persuasive cues	.020***	.027***
Informative cues	-.049***	-.046***
Brand popularity	.490***	.514***
Brand reputation	.175***	.180***
Brand type	.501***	.190***
Constant	-5.700***	-5.850***
Interaction effects		
Persuasive cues × brand type		-.172***
Informative cues × brand type		-.107***
Brand popularity × brand type		.262***
Brand reputation × brand type		.044***
R-squared	27.45%	28.84%
Adj R-squared	27.44%	28.83%

Notes: * p<0.1,** p<0.05, *** p<0.01

Table 10: Comparison of coefficients

variable 1		variable 2	Testnl: _b[variable 1]=_b[variable 2] 2]	Lincom: variable 1-variable 2
Persuasive cues	>	brand popularity	Rejected (p>0.01)	Negative (-.470), rejected (p<0.01)
Persuasive cues	>	brand reputation	Rejected (p<0.01)	Negative (-.155), rejected (p<0.01)
Informative cues	>	brand popularity	Rejected (p<0.01)	Negative (-.539), rejected (p<0.01)
Informative cues	>	brand reputation	Rejected (p<0.01)	Negative (-.223), rejected (p<0.01)
Brand popularity	>	brand reputation	Rejected (p<0.01)	Positive (0.334), supported (p<0.01)
Persuasive cues	>	information cues	Rejected (p<0.01)	Positive (0.071), supported (p<0.01)

The moderating role of brand type

To test the moderating role of brand type, we examine the impacts of the interactions of content cues and brand type on the number of likes. Table 9 shows the estimation results. H6 and H7 state that brand type negatively moderates the relationship between persuasive cues, informative cues and the liking behavior. H6 ($\beta = -0.172$, $p < 0.000$) and H7 ($\beta = -0.107$, $p < 0.000$) are supported. The moderating effects are plotted in Figure 4. The number of likes of functional brands' advertisement tweets increases rapidly when persuasive cues increase. However, that of prestige brands' tweets decreases. As informative cues increase, the number of likes also drops more sharply for prestige brands than for functional brands.

For source factors (brand popularity and reputation), H8, which claims that brand type positively moderates the influence of brand popularity on consumers' liking behavior, is supported ($\beta = 0.262$, $p < 0.000$), Figure 5(a) shows this moderating effect. As brand popularity increases, the number of likes increases more significantly for prestige brands than for functional brands. H9 is supported as expected ($\beta = 0.044$, $p < 0.000$), and the moderating effect is depicted by Figure 5(b). For prestige brands, the liking behavior exhibits greater growth speed when brand reputation increases than that for functional brands. Table 11 summarizes our findings.

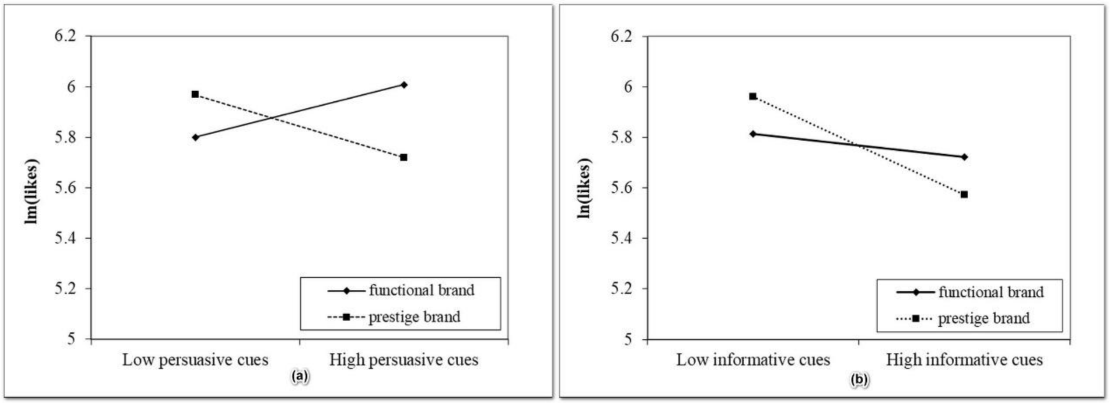

Figure 4: The moderating effect of brand type on the relationship between content factors (persuasive cues and informative cues) and the number of likes

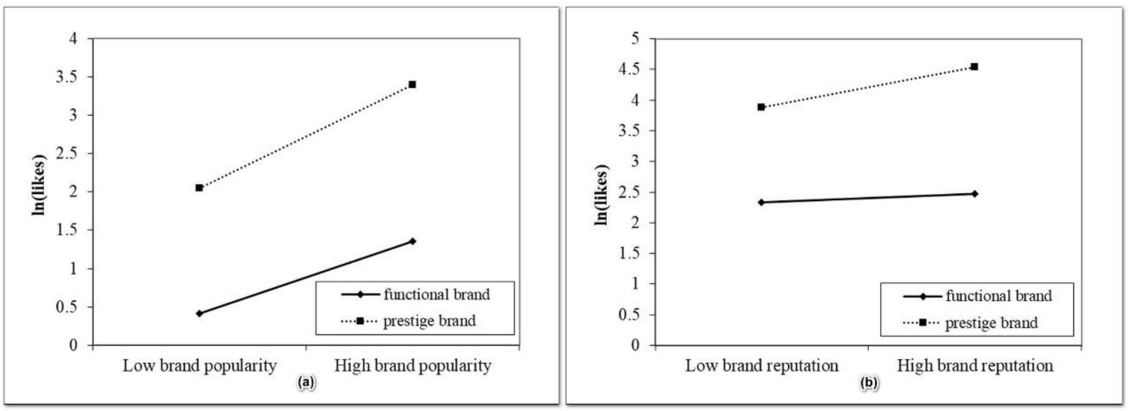

Figure 5: The moderating effect of brand type on the relationship between source factors (brand popularity and brand reputation) and the number of likes.

Table 11: Summary of the results

Hypotheses	Results
H1: Persuasive cues are positively related to consumers' liking behavior.	Supported
H2: Informative cues are positively related to consumers' liking behavior.	Not supported
H3: Brand popularity is positively related to consumers' liking behavior.	Supported
H4: Brand reputation is positively related to consumers' liking behavior.	Supported
H5: Source-related factors exert greater impacts on consumers' liking behavior toward advertisement messages than content-related factors.	Supported
H6: Brand type negatively moderates the effect of persuasive cues on consumers' liking behavior. For functional brands, persuasive cues in advertisement tweets have stronger impacts on the liking behavior.	Supported
H7: Brand type negatively moderates the effect of informative cues on consumers' liking behavior. For functional brands, informative cues in advertisement tweet have stronger impact on liking behavior.	Supported
H8: Brand type positively moderates the effects of brand popularity on consumers' liking behavior. For prestige brands, brand popularity has a stronger impact on the liking behavior.	Supported
H9: Brand type positively moderates the effects of brand reputation on consumers' liking behavior. For prestige brands, brand popularity has a stronger impact on the liking behavior.	Supported

5.4. Robustness checks

In our research context, the number of likes is arbitrary positive value. However, not every tweet can obtain likes, the dependent variable is truncated. Thus, Tobit regression model, abiding by the maximum likelihood method, may be a choice to estimate the influence of explanatory variables on the number of likes. To check the robustness of our findings, Tobit regression model is employed. Table 2 in Appendix A presents the results, which are consistent with the hierarchical regression results. Regarding the likelihood of any artificial manipulation, we employ probit model, which uses the dependent variable (the number of likes) as a binary variable to evaluate the influence of the respective factors (persuasive cues, informative cues, brand popularity, and brand reputation) on the number of likes [Cameron & Trivedi 2005]. Although this method does not permit a straightforward consideration of coefficients, we can still interpret the directions (positive or negative) of the respective factors on the likelihood of accumulating likes. The results suggest that the directions of the respective factors are consistent with our estimation (see Table 2 in Appendix A).

Furthermore, we also consider the potential endogenous bias. We suspect that an interplay exists between consumers' liking behavior and brand popularity that can lead to inconsistent estimation. Following the suggestions of former scholars [Greene 2003], brand value and quality are selected as the instrumental variables of brand popularity. The intuition is that such variables are closely related to brand popularity because it arises from brand image and word of mouth [Kim & Chung 1997]. Hence, brand value rank[3] and brand quality rank[4] are used as instruments. Moreover, creating brand pages increases brand popularity [De Vries et al. 2012] because brands can lend an ear to consumers and address their different concerns effectively by interacting with consumers. Thus, we also include the number of related Weibo accounts as an instrumental variable. We re-estimate our model by using two-stage least squares method (2SLS) [Greene 2003]. Table 3 in Appendix A reports the 2SLS estimation results, and shows comparable findings to our main analysis in Table 9. Table 3 in Appendix A also presents the endogeneity tests, which demonstrate that our instruments are valid and strong.

6. Discussion

This study contributes to the marketing literature by taking two information processing modes into consideration, which consumers may utilize to evaluate advertisements on Microblog platform. Specifically, we build on heuristic-systematic model to develop a research framework that examines how content cues and source-related factors affect the number of likes toward advertisement tweet, and how these relationships are contingent upon brand type. Eight of nine hypotheses are supported (as summarized in Table 11), delivering evidence for our most arguments. In this part, we will discuss our findings and reflect on the probable reasons for the unsupported hypotheses.

6.1. Factors affecting the likings behavior

First, we confirm that tweet content cues, namely, persuasive and informative cues, affect consumers' liking behavior. Persuasive cues are found to be positively related to consumers' liking behavior, whereas informative cues are observed to be negatively associated. These findings are consistent with the results of a recent study [Lee et al. 2018]. Previous research that focuses on individual informative cues had demonstrated their positive influences on message likes [Swani & Milne 2017]. However, the prevalent use of such cues may be detrimental to advertisement effectiveness, which is measured by the number of likes. One possible reason is that too much of these cues all at once may be treated as direct selling, which can destroy consumers' browsing experience on the platform. It is similar to the context that too much advertisements can impair the TV viewing experience. Another reason may be that consumers will have unpleasant feelings to the served ads about prices and sales when log into the platform for social interactions and current affairs.

Second, we conduct an additional analysis in which two composite summary variables, namely, persuasive and informative cues are unfolded. We rerun our regression model to explore the relationships between individual content cue and the number of likes toward tweets. We further demonstrate that brand personality-related contents are significant and positively related to the liking behavior, namely, humor and emotional appeal, brands' philanthropic positioning are also positively associated with the number of likes. These findings are consistent with those of a preceding study [Lee et al. 2018]. In addition, mentioning a remarkable fact, incorporating an emotional appeal and emoticon, and small talk drive consumers to click the "like" button. With regard to informative cues, we find that tweets that mention a specific product, offer any type of discounts, freebies, or sweepstakes, contain information about product availability are more likely to obtain likes (see Table 1 in Appendix A).

Third, we explore the influence of the characteristics of tweet source (brand popularity and reputation) on the number of likes. As we hypothesize, brand popularity and reputation both have positive impacts on consumers' liking behavior. In addition, our results show that brand popularity is more powerful in increasing the number of likes than brand reputation. It is probably because consumers on social media are more influenced by social norms [Steyn et al. 2010; Kim & Min 2016] concerning about what most people approve of and what most people do. Another possible reason may be that the distinction between online and offline brand "consumption", the brand that consumers "like"

[3] https://brandirectory.com/rankings/automobiles-100-2018
[4] https://k.autohome.com.cn/complex/brand

on social media may never be owned offline [Sekhon et al. 2015]. So the influence of brand popularity on the number of likes is stronger than brand reputation.

Furthermore, we confirm that source factors exert greater impacts on consumers' liking behavior on advertisement message than tweet content-related factors. It is in accordance with our hypothesis and proves the rationality of our arguments.

To sum up, brand popularity is the most powerful factor in motivating consumers to like the advertisement. Then it is brand reputation in increasing the number of likes. The third is persuasive cues, as they have positive influence on likes. Lastly, it is informative cues which exert negative impact on consumers' liking behavior.

6.2. The role of brand type in consumers' liking behavior

In our study, the moderating role of brand type is explored. Auto brands are classified into two types: functional or prestige brands, according to the definition of Park et al. [1991]. We find that brand type is a negative moderator in the relationship between content cues and the number of likes, and persuasive cues have a more powerful influence for functional brands. However, the impact of informative cues decreases the number of likes, and it is more evident for prestige brands than functional brands. The reason may be that informative cues are more ubiquitously used by prestige brands than by functional brands. Moreover, the impacts of the persuasive cues of different brand types are in opposite directions, as illustrated in Figure 4(a), for prestige brands, as persuasive cues increase, the number of likes significantly drops. This condition is opposite to that for functional brands because prestige brands are often well regarded or well known. Consumer tends to know prestige brands better than functional brands at a certain degree. In social media, persuasive cues (e.g., celebrity) may be more influential for unfamiliar brands than for familiar brands [Wood & Burkhalter 2014]. Hence, in the case of prestige brands, the frequently used persuasive cues exert negative impacts on consumers' liking behavior. The effect of brand popularity on the liking behavior is positively moderated by brand type. We plot the interactions between brand type and brand popularity in Figure 5(a). For prestige brands, as brand popularity increases, the number of likes grows faster than for functional brands. The condition is the same with brand reputation, which is also positively moderated by brand type. As displayed in Figure 5(b), the influence of prestige brands' reputation is much stronger than functional brands' reputation in driving consumers to like the tweets. The reason is that the prestige concept is more widely known and generalizable than the functional concept.

7. Implications and limitations

7.1. Theoretical implications

This study provides several theoretical implications.

First, recent studies have paid attention to the role of post/message content by classifying posts/messages into self-defined categories employing coders or Turkers [De Vries et al. 2012; Kim et al. 2015; Vargo 2016; Schultz 2017]. Posts/messages may include various hints of diverse categories. Thus, assigning posts/messages into two or more categories is a complicated and tough task for coders or Turkers. The number of samples is limited, and the research costs are high. In this article, tweets are analyzed at the content level by means of joining manual coding with machine learning algorithms, and we manage to achieve over 90% accuracy. The influence of content factors (persuasive and informative cues) on consumers' liking behavior toward advertisement tweets in microblogs is explored. Our proposed methods will be helpful in future studies to realize the empirical analysis on relatively large-scale datasets.

Second, previous empirical investigations on consumers' liking behavior have focused on post/message content, leaving the source characteristics of posts/messages unexplored [De Vries et al. 2012; Kim et al. 2015; Vargo 2016; Schultz 2017; Lee et al. 2018]. To address this research gap, we indicate that tweet content and the ones who post tweets should be considered simultaneously in enhancing the number of likes. In contrast to other studies concentrating on the content aspects of posts/messages (e.g., predefined post categories, content orientations, and tweet typology), our research is the first to explore the influence of source characteristics. Drawing on HSM, we demonstrate that the source characteristics (i.e., brand popularity and reputation) of advertisement tweets can predict consumers' liking behavior. Similarly, scholars have recognized the important role of source in consumers' behavior [Li et al. 2013; Wang et al. 2018]. For example, Li et al. [2013] found that source-based review features have direct impacts on review helpfulness. Wang et al. [2018] revealed that source credibility has significant effects on repost behavior. Dou et al. [2012] examined how the source of a product review influences consumers' product judgments. We contribute to this area by exploring specific source characteristics in consumers' liking behavior on social media. Our findings raise the importance of source characteristics in driving consumers to click "like", wherein brand popularity and reputation positively influence the number of likes.

Third, our research results enrich the understanding of how content cues and source-related factors affect consumers' liking behavior. Although source-related characteristics and content-related characteristics all significantly affects the number of likes, these impacts are different in effect size and effect direction in influencing consumers' liking behavior toward advertisement. Specifically, persuasive cues are positively related to the number of likes while information cues decrease the number of likes. Although some particular informative cues (e.g., corporate name and brand name) increase the number of likes [Swani & Milne 2017], our findings suggest that too much is as bad as too little. Moreover, we first explore the impacts of source characteristics on consumers' liking behavior toward advertisements. The results show that brand popularity and brand reputation are both significant predictors of consumers' liking behavior. Furthermore, brand popularity exerts stronger impact on the number of likes. Although it has been demonstrated brand popularity and brand reputation affect advertisement evaluation [Walsh et al. 2009; Whang et al. 2015], our findings provide deeper insights that their effect size is different.

Forth, this research enhances the understanding of the moderating role of brand type (functional vs. prestige brand) on consumers' liking behavior. Brand type has been an important role in brand extension [Park et al. 1991; Lye et al. 2001; Monga & John 2010]. By extending the understanding of brand type into the context of microblog, we examine how the interactions between brand type and other factors affect the number of likes. We further clarify the contextual boundary of the proposed relationships. For example, we find that the positive influence of source factors (brand popularity and reputation) varies, depending on brand type. Although previous study indicated that brand popularity could result in negative brand evaluation because of congestion loss of exclusivity for symbolic products [Kim & Min 2016], our results show that this problem is not critical in social media context (e.g., in microblogs), prestige brand enhances the impact of brand popularity on consumers' liking behavior. We also contribute to the literature by revealing that persuasive cues exert stronger negative impacts on the number of likes for prestige brands and stronger positive effects for functional brands. These findings have verified our hypotheses and shed light on the boundary condition for predicting the relationships among persuasive cues, informative cues, brand popularity, brand reputation, and the number of likes. Thus, we obtain a nuanced understanding of the roles of the related factors in stimulating consumers to like advertisement tweets.

7.2. Practical implications

Managing advertisements on social media is necessary. To make advertisements effective, exploring the factors affecting consumers' liking behavior toward advertisements is of great importance. Advertisers should be aware of these factors. Therefore, knowledge on such factors has become essential to improve the effectiveness of advertisements on social media. Our findings give suggestions to brand managers and advertisers who have adopted social media marketing strategies.

Firstly, with regard to content-related characteristics, we find that persuasive cues are positively related to consumers' liking behavior, whereas informative cues are observed to be negatively associated with the number of likes. So we suggest that brand managers should strive to use persuasive cues and prevent prevalent use of informative cues. Source-related characteristics (brand popularity and brand reputation) both have positive influence on consumers' liking behavior. So brand managers are encouraged to exhibit brand popularity and brand reputation, especially brand popularity, because it exerts stronger impact on the number of likes than brand reputation.

Our results can also provide guidance in the implementation of advertisements for different brand types. Brand type moderates the effects of antecedent factors on consumers' liking behavior toward advertisement tweets. Therefore, we suggest that related brands should design customized advertisement tweets to engage consumers according to their brand type. With regard to the design of advertisement tweets for prestige brands, we give the following suggestions, because the impacts of brand popularity and reputation on the number of likes are strengthened. Advertisers should also preferentially exhibit brand popularity and reputation. Moreover, content factors (i.e., persuasive and informative cues) are found to be negatively related to the number of likes for prestige brands. Thus, we suggest that brand managers should be careful in selecting content cues because the increase of these factors can result in the decrease of the number of likes. As demonstrated in our additional analysis in Appendix A, brand personality-related content cues, remarkable facts, emotional appeals, and emoticons are recommended when selecting content cues. Certain informative cues, such as mentioning specific products, offering discounts, freebies, or sweepstakes, and containing information about product availability can also be included in the tweets. Managers of prestige brand should cast caution to the number of content cues because as they increase, the number of likes decreases. In addition, the positive effects of brand popularity and brand reputation are enhanced by prestige brand, so prestige brands are suggested to display brand popularity and brand reputation, in particular, brand popularity.

In designing advertisement tweets for functional brands, advertisers are suggested to employ persuasive cues in advertisement tweets. It is because that in the case of functional brands, persuasive cues have stronger positive impacts on the number of likes. Hence, persuasive cues, such as brand personality-related content cues, remarkable facts, emotional appeals, and emoticons, and small talks are recommended. These persuasive cues are positively related to the number of likes. We also suggest brand managers to exhibit brand popularity and reputation because both factors exert significant and positive impacts on consumers' liking behavior. We do not suggest that advertisers develop advertisement tweets by using too many informative cues. Our findings indicate that informative cues have a significantly negative influence on the number of likes for functional brands.

7.3. Limitations

Similar to any research, this study is subject to certain limitations. First, the dataset collected from Weibo is from one industry only (i.e., auto industry). Future studies can explore the degree to which our findings can be extended to other industries or other microblog platforms. That is, future studies can test the generality of our findings for different industries on other platforms.

Second, we consider the factors of advertisement content and initiator. The inclusion of consumers' related variables, who are exposed to advertisements, in the model can be a practical extension of our research. These variables (e.g., gender and motivations) can affect the liking behavior [Gan 2017; Chiang 2020]. Moreover, personality traits have demonstrated significant effects on consumers' online behaviors (like, comment, and share) in different social platforms [Kabadayi & Price 2014; Lee et al. 2014]. Future research can examine these factors and explore whether similar consumers behave similarly toward advertisements.

Future research can also investigate the relationship among consumers because peer recognition and social cognation are expected to affect consumers' behavior [Forman et al. 2008; Cheung et al. 2014]. When a consumer clicks the like button, his/her friends can see this action and may be influenced. Therefore, investigating how consumers' behavior toward advertisements is affected by peers' behavior can be valuable and interesting.

8. Conclusions

This study examines the impact of content cues (persuasive and informative cues) and source factors (brand popularity and reputation) on consumers' liking behavior toward advertisements. We also investigate how brand type (functional or prestige brand) moderates the above relationships. More than 240,000 tweets of 67 different brands from Weibo are used to test the proposed hypotheses. Manual coding and machine learning algorithms are integrated to develop a classification model for processing this relatively large-scale data. After processing and analyzing such data, we obtain the following conclusions.

First, the significant relationships between content cues (i.e., persuasive and informative cues) and consumers' liking behavior are confirmed. Specifically, persuasive cues positively stimulate consumers' liking behavior, whereas informative cues are negatively related to tweet liking.

Second, the relationships between source factors and the number of likes are verified. We compare the power of content cues with source factors in driving consumers to click "like". The expected results are attained. Source factors are found more powerful in motivating consumers to like advertisements than content cues.

Third, to provide further insights for the effects of the proposed factors, the coefficients comparisons are conducted. The results show that brand popularity exerts a stronger impact on consumers' liking behavior than brand reputation. Hence the order of effect size in increasing the number of likes from big to small is brand popularity, brand reputation, persuasive cues and finally with informative cues which negatively impacts the number of likes.

Fourth, brand type plays as a moderator. The relationships between content factors (i.e., persuasive and informative cues) and the number of likes are negatively moderated by brand type. Particularly, for functional brands, with the increase of persuasive cues the number of likes increases which is opposite to prestige brands. With regard to informative cues, the increase of such cues lead to the decrease of likes especially for prestige brands. In addition, brand type positively moderates the relationship between source factors (i.e., brand popularity and reputation) and consumers' liking behavior. In contrast to functional brands, brand popularity and reputation exert stronger power in enhancing the number of likes for prestige brands.

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REFERENCES

Aaker Jennifer, "Dimensions of Brand Personality," *Journal of Marketing Research*, Vol. 34, No. 3:347-356, 1997.

Armstrong J Scott. Persuasive Advertising: Evidence-based Principles: Palgrave Macmillan, 2010.

Baek Tae Hyun, Kim Jooyoung, Yu Jay Hyunjae, "The Differential Roles of Brand Credibility and Brand Prestige in Consumer Brand Choice," *Psychology & Marketing*, Vol. 27, No. 7:662-678, 2010.

Baker William E, Lutz Richard J, "An Empirical Test of an Updated Relevance-accessibility Model of Advertising Effectiveness," *Journal of Advertising*, Vol. 29, No. 1:1-14, 2000.

Bennett Paul N. "Building Reliable Metaclassifiers for Text Learning", 2006.

Berger Jonah, Milkman Katherine L, "What makes Online Content Viral?," *Journal of Marketing Research*, Vol. 49, No. 2:192-205, 2012.

Bhattacherjee Anol, Sanford Clive, "Influence Processes for Information Technology Acceptance: An Elaboration Likelihood Model," *MIS Quarterly*, Vol. 30, No. 4:805-825, 2006.

Blackston Max, "The Qualitative Dimension of Brand Equity," *Journal of Advertising Research*, Vol. 35, No. 4:RC2-RC7, 1995.

Cameron A Colin, Trivedi Pravin K. Microeconometrics: Methods and Applications: Cambridge university press, 2005.

Chaiken Shelly, "Heuristic versus Systematic Information Processing and The Use of Source versus Message Cues in Persuasion," *Journal of Personality and Social Psychology*, Vol. 39, No. 5:752, 1980.

Chaiken Shelly, "Heuristic and Systematic Information Processing Within and Beyond The Persuasion Context," *Unintended Thought*, 212-252, 1989.

Chan Kara, Leung Ng Yu, Luk Edwin K, "Impact of Celebrity Endorsement in Advertising on Brand Image among Chinese Adolescents," *Young Consumers*, Vol. 14, No. 2:167-179, 2013.

Chaudhuri Arjun, "How Brand Reputation Affects the Advertising-brand Equity Link," *Journal of Advertising Research*, Vol. 42, No. 3:33-43, 2002.

Chen Serena, Chaiken Shelly, "The Heuristic-systematic Model in Its Broader Context," *Dual-process Theories in Social Psychology*, Vol. 15:73-96, 1999.

Cheung Christy MK, Xiao Bo Sophia, Liu Ivy LB, "Do Actions Speak louder than Voices? The Signaling Role of Social Information Cues in Influencing Consumer Purchase Decisions," *Decision Support Systems*, Vol. 65:50-58, 2014.

Cheung Cindy Man-Yee, Sia Choon-Ling, Kuan Kevin KY, "Is this Review Believable? A Study of Factors affecting the Credibility of Online Consumer Reviews from an ELM Perspective," *Journal of the Association for Information Systems*, Vol. 13, No. 8:618, 2012.

Chiang C.T., Yang M.H., Koo T.L., Liao C.H., "What drives customer engagement behavior? The impact of user participation from a sociotechnical perspective," *Journal of Electronic Commerce Research*, Vol. 21, No. 3:197-214, 2020.

Cialdini Robert B, "Harnessing The Science of Persuasion," *Harvard Business Review*, Vol. 79, No. 9:72-81, 2001.

Cotte June, Coulter Robin A, Moore Melissa, "Enhancing or Disrupting guilt: The Role of ad Credibility and Perceived Manipulative Intent," *Journal of Business Research*, Vol. 58, No. 3:361-368, 2005.

Davis Joshua M, Tuttle Brad M, "A Heuristic–systematic Model of End-user Information Processing When Encountering IS Exceptions," *Information & Management*, Vol. 50, No. 2-3:125-133, 2013.

Davis Scott W, Horváth Csilla, Gretry Anaïs, Belei Nina, "Say What? How The Interplay of Tweet Readability and Brand Hedonism Affects Consumer Engagement," *Journal of Business Research*, Vol. 100: 150-164, 2019.

De Vries Lisette, Gensler Sonja, Leeflang Peter SH, "Popularity of Brand Posts on Brand Fan Pages: An Investigation of the Effects of Social Media Marketing," *Journal of Interactive Marketing*, Vol. 26, No. 2:83-91, 2012.

Dean Dwane Hal, "Brand Endorsement, Popularity, and Event Sponsorship as Advertising Cues Affecting Consumer Pre-purchase Attitudes," *Journal of Advertising*, Vol. 28, No. 3:1-12, 1999.

Dou Xue, Walden Justin A, Lee Seoyeon, Lee Ji Young, "Does Source Matter? Examining Source Effects in Online Product Reviews," *Computers in Human Behavior*, Vol. 28, No. 5:1555-1563, 2012.

Eagly Alice H, Chaiken Shelly. The Psychology of Attitudes: Harcourt Brace Jovanovich College Publishers, 1993.

Eisend Martin, "A Meta-analysis of Humor in Advertising," *Journal of the Academy of Marketing Science*, Vol. 37, No. 2:191-203, 2009.

eMarketer, "Sina Weibo Net Ad Revenues in China, 2016-2020 (billions, % change and % of total digital ad spending)," , 2018a.

eMarketer, "Weibo Now Used by Nearly 25% of Population in China,", 2018b.

Forman Chris, Ghose Anindya, Wiesenfeld Batia, "Examining the Relationship between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets," *Information Systems Research*, Vol. 19, No. 3:291-313, 2008.

Fornell Claes, Larcker David F, "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," *Journal of Marketing Research*, Vol. 18, No. 1:39-50, 1981.

Gan Chunmei, "Understanding WeChat Users' Liking Behavior: An Empirical Study in China," *Computers in Human Behavior*, Vol. 68:30-39, 2017.

Geva Hilah, Oestreicher-Singer Gal, Saar-Tsechansky Maytal, "Using Retweets When Shaping Our Online Persona: Topic Modeling Approach," *MIS Quarterly*, Vol. 43, No. 2, 2019.

Gnyawali Devi R, Fan Weiguo, Penner James, "Competitive Actions and Dynamics in the Digital Age: An Empirical Investigation of Social Networking Firms," *Information Systems Research*, Vol. 21, No. 3:594-613, 2010.

Goh Khim Yong, Heng Cheng Suang, Lin Zhijie, "Social Media Brand Community and Consumer Behavior: Quantifying the Relative Impact of User- and Marketer-Generated Content," *Information Systems Research*, Vol. 24, No. 1:88-107, 2013.
Greene William H. Econometric analysis: Pearson Education India, 2003.
Grossman Gene M, Shapiro Carl, "Informative Advertising with Differentiated Products," *The Review of Economic Studies*, Vol. 51, No. 1:63-81, 1984.
Hanzaee Kambiz Heidarzadeh, Taghipourian Mohammad Javad, "The Effects of Brand Credibility and Prestige on Consumers Purchase Intention in Low and High Product Involvement," *Journal of Basic and Applied Scientific Research*, Vol. 2, No. 2:1281-1291, 2012.
Heimbach Irina, Hinz Oliver, "The Impact of Content Sentiment and Emotionality on Content Virality," *International Journal of Research in Marketing*, Vol. 33, No. 3:695-701, 2016.
Hellofs Linda L, Jacobson Robert, "Market Share and Customers' Perceptions of Quality: When can Firms grow Their way to Higher versus Lower Quality?," *Journal of Marketing*, Vol. 63, No. 1:16-25, 1999.
Hollenbeck Candice R, Kaikati Andrew M, "Consumers' Use of Brands to Reflect Their Actual and Ideal Selves on Facebook," *International Journal of Research in Marketing*, Vol. 29, No. 4:395-405, 2012.
Hovland Carl Iver, Janis Irving L, Kelley Harold H. Communication and Persuasion: Psychological Studies of Opinion Change: Yale University Press, 1953.
Kabadayi Sertan, Price Katherine, "Consumer–brand Engagement on Facebook: Liking and Commenting behaviors," *Journal of Research in Interactive Marketing*, Vol. 8, No. 3:203-223, 2014.
Karniouchina Ekaterina V, "Impact of Star and Movie Buzz on Motion Picture Distribution and Box Office Revenue," *International Journal of Research in Marketing*, Vol. 28, No. 1:62-74, 2011.
Keller Kevin Lane, "Conceptualizing, Measuring, and Managing Customer-based Brand Equity," *Journal of Marketing*, Vol. 57, No. 1:1-22, 1993.
Keller Kevin Lane, Lehmann Donald R, "Brands and Branding: Research Findings and Future Priorities," *Marketing Science*, Vol. 25, No. 6:740-759, 2006.
Keller Kevin Lane, Parameswaran MG, Jacob Isaac. Strategic Brand Management: Building, Measuring, and Managing Brand Equity: Pearson Education India, 2011.
Kim Angella J, Ko Eunju, "Do Social Media Marketing Activities Enhance Customer Equity? An Empirical Study of Luxury Fashion Brand," *Journal of Business Research*, Vol. 65, No. 10:1480-1486, 2012.
Kim Cheonsoo, Yang Sung-Un, "Like, Comment, and Share on Facebook: How each Behavior Differs from the Other," *Public Relations Review*, Vol. 43, No. 2:441-449, 2017.
Kim Chung Koo, Chung Jay Young, "Brand Popularity, Country Image and Market Share: An Empirical Study," *Journal of International Business Studies*, Vol. 28, No. 2:361-386, 1997.
Kim Daehee, Spiller Lisa D, Hettche Matt, "Analyzing Media Types and Content Orientations in Facebook for Global Brands," *Journal of Research in Interactive Marketing*, Vol. 9, No. 1:4-30, 2015.
Kim Ji□Hern, Min Dongwon, "The Effects of Brand Popularity as An Advertising Cue on Perceived Quality in the Context of Internet Shopping," *Japanese Psychological Research*, Vol. 56, No. 4:309-319, 2014.
Kim Ji□Hern, Min Dongwon, "Consumers'Response to an Advertisement Using Brand Popularity in a Foreign Market," *Japanese Psychological Research*, Vol. 58, No. 4:342-354, 2016.
Kim Jungkeun, Kim Jae-Eun, Marshall Roger, "Are Two Arguments always Better than One? Persuasion Knowledge Moderating the Effect of Integrated Marketing Communications," *European Journal of Marketing*, Vol. 50, No. 7/8:1399-1425, 2016.
Kirmani Amna, Sood Sanjay, Bridges Sheri, "The Ownership Effect in Consumer Responses to Brand Line Stretches," *Journal of Marketing*, Vol. 63, No. 1:88-101, 1999.
Koo Kim Chung, "Brand Popularity and Country Image in Global Competition: Managerial Implications," *Journal of Product & Brand Management*, Vol. 4, No. 5:21-33, 1995.
Kumar Ashish, Bezawada Ram, Rishika Rishika, Janakiraman Ramkumar, Kannan PK, "From Social to Sale: The Effects of Firm-generated Content in Social Media on Customer Behavior," *Journal of Marketing*, Vol. 80, No. 1:7-25, 2016.
Labrecque Lauren I, Milne George R, "Exciting Red and Competent Blue: the Importance of Color in Marketing," *Journal of the Academy of Marketing Science*, Vol. 40, No. 5:711-727, 2012.
Lee Dokyun, Hosanagar Kartik, Nair Harikesh S, "Advertising Content and Consumer Engagement on Social Media: Evidence from Facebook," *Management Science*, Vol. 64, No.:5105-5131, 2018.
Lee Eunsun, Ahn Jungsun, Kim Yeo Jung, "Personality Traits and Self-presentation at Facebook," *Personality and Individual Differences*, Vol. 69, No.:162-167, 2014.
Lee Shu-Yueh, Hansen Sara Steffes, Lee Jin Kyun, "What makes us click "like" on Facebook? Examining

Psychological, Technological, and Motivational Factors on Virtual Endorsement," *Computer Communications*, Vol. 73, No.:332-341, 2016.

Leung Xi Y, Bai Billy, Erdem Mehmet, "Hotel Social Media Marketing: A Study on Message Strategy and Its Effectiveness," *Journal of Hospitality and Tourism Technology*, Vol. 8, No. 2:239-255, 2017.

Li Mengxiang, Huang Liqiang, Tan Chuan-Hoo, Wei Kwok-Kee, "Helpfulness of Online Product Reviews as Seen by Consumers: Source and Content Features," *International Journal of Electronic Commerce*, Vol. 17, No. 4:101-136, 2013.

Li Yiyi, Xie Ying, "Is a Picture Worth a Thousand Words? An Empirical Study of Image Content and Social Media Engagement," *Journal of Marketing Research*, Vol. 57, No. 1:1-19, 2020.

Logan Kelty, Bright Laura F, Gangadharbatla Harsha, "Facebook versus Television: Advertising Value Perceptions Among Females," *Journal of Research in Interactive Marketing*, Vol. 6, No. 3:164-179, 2012.

Luarn Pin, Lin Yu-Fan, Chiu Yu-Ping, "Influence of Facebook Brand-page Posts on Online Engagement," *Online Information Review*, Vol. 39, No. 4:505-519, 2015.

Lye Ashley, Venkateswarlu Pulakanam, Barrett Jo, "Brand Extensions: Prestige Brand Effects," *Australasian Marketing Journal (AMJ)*, Vol. 9, No. 2:53-65, 2001.

Magnini Vincent P, Karande Kiran, Singal Manisha, Kim Dohee, "The Effect of Brand popularity Statements on Consumers' Purchase Intentions: The Role of Instrumental Attitudes Toward the Act," *International Journal of Hospitality Management*, Vol. 34, No.(Com):160-168, 2013.

Majchrzak Ann, Jarvenpaa Sirkka L, "Safe Contexts for Interorganizational Collaborations Among Homeland Security Professionals," *Journal of Management Information Systems*, Vol. 27, No. 2:55-86, 2010.

MarketingToChina, "a Guide to Weibo Advertising,", 2017.

Meyers-Levy Joan, Maheswaran Durairaj, "Exploring Message Framing Outcomes When Systematic, Heuristic, or Both Types of Processing Occur," *Journal of Consumer Psychology*, Vol. 14, No. 1-2:159-167, 2004.

Mitra Debanjan, Golder Peter N, "How Does Objective Quality Affect Perceived Quality? Short-term Effects, Long-term effects, and Asymmetries," *Marketing Science*, Vol. 25, No. 3:230-247, 2006.

Monga Alokparna Basu, John Deborah Roedder, "What Makes Brands Elastic? The influence of Brand Concept and Styles of Thinking on Brand Extension Evaluation," *Journal of Marketing*, Vol. 74, No. 3:80-92, 2010.

Morrin Maureen, "The Impact of Brand Extensions on Parent Brand Memory Structures and Retrieval Processes," *Journal of Marketing Research*, Vol. 36, No. 4:517-525, 1999.

Muntinga Daniël G, Moorman Marjolein, Smit Edith G, "Introducing COBRAs: Exploring Motivations for Brand-related Social Media Use," *International Journal of Advertising*, Vol. 30, No. 1:13-46, 2011.

Newswire PR, "Social Media Advertising Spend in the U.S.," , 2016.

Park C Whan, Milberg Sandra J, Lawson Robert, "Evaluation of Brand Extensions: The Role of Product Feature Similarity and Brand Concept Consistency," *Journal of Consumer Research*, Vol. 18, No. 2:185-193, 1991.

Petty Richard E, Cacioppo John T. Communication and Persuasion: Central and Peripheral Routes to Attitude Change: Springer Science & Business Media, 2012.

Petty Richard E, Cacioppo John T, Schumann David, "Central and Peripheral Routes to Advertising Effectiveness: The Moderating Role of Involvement," *Journal of Consumer Research*, Vol. 10, No. 2:135-146, 1983.

Rauschnabel Philipp A, Praxmarer Sandra, Ivens Bjorn S. Social Media Marketing: How Design Deatures Influence Interactions with Brand Postings on Facebook. Advances in Advertising Research (Vol III): Springer, 2012. pp. 153-161.

Resnik Alan, Stern Bruce L, "An Analysis of Information Content in Television Advertising," *Journal of Marketing*, Vol. 41, No. 1:50-53, 1977.

Rokach Lior, "Ensemble-based Classifiers," *Artificial Intelligence Review*, Vol. 33, No. 1:1-39, 2010.

Sabate Ferran, Berbegal-Mirabent Jasmina, Cañabate Antonio, Lebherz Philipp R, "Factors Influencing Popularity of Branded Content in Facebook Fan Pages," *European Management Journal*, Vol. 32, No. 6:1001-1011, 2014.

Santilli Paul C, "The Informative and Persuasive Functions of Advertising: A Moral Appraisal," *Journal of Business Ethics*, Vol. 2, No. 1:27-33, 1983.

Schultz Carsten D, "Proposing to Your Fans: Which Brand Post Characteristics Drive Consumer Engagement Activities on Social Media Brand Pages?," *Electronic Commerce Research and Applications*, Vol. 26:23-34, 2017.

Schulze Christian, Schöler Lisa, Skiera Bernd, "Not all Fun and Games: Viral Marketing for Utilitarian Products," *Journal of Marketing*, Vol. 78, No. 1:1-19, 2014.

Sekhon Tejvir, Bickart Barbara, Trudel Remi, Fournier Susan. Being a Likable Braggart: How Consumers Use Brand Mentions for Self-Presentation on Social Media, 2015.

Seo Yuri, Kim Jungkeun, Choi Yung Kyun, Li Xiaozhu, "In "likes" We Trust: Likes, Disclosures and Firm-serving Motives on Social Media," *European Journal of Marketing*, 2019.

Sichtmann Christina, "An Analysis of Antecedents and Consequences of Trust in a Corporate Brand," *European Journal of Marketing*, Vol. 41, No. 9/10:999-1015, 2007.

Steyn Peter, Wallström Åsa, Pitt Leyland, "Consumer-generated Content and Source Effects in Financial Services Advertising: An Experimental Study," *Journal of Financial Services Marketing*, Vol. 15, No. 1:49-61, 2010.

Stock James H, Yogo Motohiro. Testing for Weak Instruments in Linear Iv Regression. Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg: Cambridge University Press, 2005. pp. 80-108.

Sun Jianshan, Wang Gang, Cheng Xusen, Fu Yelin, "Mining affective Text to improve Social Media Item Recommendation," *Information Processing and Management*, Vol. 51, No. 4:444-457, 2015.

Sussman Stephanie Watts, Siegal Wendy Schneier, "Informational Influence in Organizations: An Integrated Approach to Knowledge Adoption," *Information Systems Research*, Vol. 14, No. 1:47-65, 2003.

Swani Kunal, Milne George R, "Evaluating Facebook Brand Content Popularity for Service versus Goods Offerings," *Journal of Business Research*, Vol. 79:123-133, 2017.

Todorov Alexander, Chaiken Shelly, Henderson Marlone D, "The Heuristic-systematic Model of Social Information Processing," *The Persuasion Handbook: Developments in Theory and Practice*, 195-211, 2002.

Triandis Harry Charalambos, "Attitude and Attitude Change. Wiley Foundations of Social Psychology Series," ,1971.

Tucker Catherine E, "The Reach and Persuasiveness of Viral Video Ads," *Marketing Science*, Vol. 34, No. 2:281-296, 2014.

Vargo Chris J, "Toward a Tweet Typology: Contributory Consumer Engagement With Brand Messages by Content Type," *Journal of Interactive Advertising*, Vol. 16, No. 2:157-168, 2016.

Verhoef Peter C, Langerak Fred, Donkers Bas, "Understanding Brand and Dealer Retention in the New Car Market : The Moderating Role of Brand Tier," *Journal of Retailing*, Vol. 83, No. 1:97-113, 2007.

Wagner Timm F, Baccarella Christian V, Voigt Kai-Ingo, "Framing Social Media Communication: Investigating the Effects of Brand Post Appeals on User Interaction," *European Management Journal*, Vol. 35, No. 5:606-616, 2017.

Walsh Gianfranco, Mitchell Vincent□Wayne, Jackson Paul R, Beatty Sharon E, "Examining the Antecedents and Consequences of Corporate Reputation: A Customer Perspective," *British Journal of Management*, Vol. 20, No. 2:187-203, 2009.

Wang Lei, Qian Da, Zhu Lin, "The Effect of System Generated Cues on Microblog Rewarding Repost Behavior–a Source Credibility Perspective," *Journal of Electronic Commerce Research*, Vol. 19, No. 1:104, 2018.

Wang Zhisheng, Li Huiying, Ye Qiang, Law Rob, "Saliency Effects of Online Reviews Embedded in the Description on Sales: Moderating Role of Reputation," *Decision Support Systems*, Vol. 87:50-58, 2016.

Watts Stephanie A, Zhang Wei, "Capitalizing on Content: Information Adoption in Two Online Communities," *Journal of the Association for Information Systems*, Vol. 9, No. 2:3, 2008.

Weinberger Marc G, Gulas Charles S, "The Impact of Humor in Advertising: A Review," *Journal of Advertising*, Vol. 21, No. 4:35-59, 1992.

Whang Haesung, Ko Eunju, Zhang Ting, Mattila Pekka, "Brand Popularity as an Advertising Cue Affecting Consumer Evaluation on Sustainable Brands: A Comparison Study of Korea, China, and Russia," *International Journal of Advertising*, Vol. 34, No. 5:789-811, 2015.

Wilson Elizabeth J, Sherrell Daniel L, "Source Effects in Communication and Persuasion Research: A Meta-analysis of Effect Size," *Journal of the Academy of Marketing Science*, Vol. 21, No. 2:101, 1993.

Wood Natalie T, Burkhalter Janée N, "Tweet This, not That: A Comparison Between Brand Promotions in Microblogging Environments Using Celebrity and Company-generated Tweets," *Journal of Marketing Communications*, Vol. 20, No. 1-2:129-146, 2014.

Yin Chunxiao, Sun Yongqiang, Fang Yulin, Lim Kai, "Exploring the Dual-role of Cognitive Heuristics and The Moderating Effect of Gender in Microblog Information Credibility Evaluation," *Information Technology & People*, Vol. 31, No. 3:741-769, 2018.

Yin Guopeng, Wei Li, Xu Wei, Chen Minder. "Exploring Heuristic Cues for Consumer Perceptions of Online Reviews Helpfulness: the Case of Yelp.Com", *PACIS*, 2014.

YouGov, "Twitter giveaways are an easy way to increase customer engagement " , 2019.

Zell Anne L, Moeller Lisa, "Are You Gappy for Me… on Facebook? The Potential Importance of “likes” and Comments," *Computers in Human Behavior*, Vol. 78:26-33, 2018.

Zhang Kem ZK, Zhao Sesia J, Cheung Christy MK, Lee Matthew KO, "Examining the Influence of Online Reviews on Consumers' Decision-making: A Heuristic-systematic Model," *Decision Support Systems*, Vol. 67:78-89, 2014.

AppendixA

Table 1: Additional analysis

Persuasive cues:	
Mention remarkable fact	.037***
Present any type of emotion (emotional appeal)	.022*
Contain emoticon or net slang	.146***
Mention holidays	-.025***
Use celebrity	-.172***
Humor used	.216***
Philanthropic or activist related	.066***
Contain small talk other than product or brand business	.042***
Informative cues:	
Mention a brand or organization name	-.069***
Mention specific product	.068***
Offer any type of discounts or freebies, sweepstakes	.042***
Compare price or makes price match guarantee	-.136***
Contain product price	-.025***
Contain targeted audience	-.100***
Contain information on product availability (e.g., stock or release date)	.064***
Contain information on where to obtain product	-.031***
Brand popularity	.510***
Brand reputation	.175***
Brand type	.179***
Tweet length	.001**
Photo	.078***
Video	.765***
Link	-.347***
Logfans	.155***
Grade	.003***
Constant	-5.764***
Persuasive cues × brand type	-.167***
Informative cues × brand type	-.113***
Brand popularity × brand type	.263***
Brand reputation × brand type	.070***
R-squared	25.93%
Adjusted R-squared	25.92%

Notes: * $p<0.1$,** $p<0.05$, *** $p<0.01$

Table 2: The results of Tobit and Probit regression

Variables	Tobit regression	Probit regression
Persuasive cues	.027***(.003)	.002*** (.003)
Informative cues	-.052***(.003)	-.029*** (.003)
Brand popularity	.593***(.006)	.340*** (.007)
Brand reputation	.178***(.006)	.089*** (.006)
Brand type	.322***(.027)	.128*** (.034)
Tweet length	.001***(.000)	.001*** (.000)
Photo	.080***(.010)	.120*** (.010)
Video	.837***(.020)	.515*** (.026)
Link	-.429***(.015)	-.268*** (.015)
Logfans	.197***(.004)	.096*** (.004)
Grade	.007***(.001)	.014*** (.001)
Constant	-7.316***(.063)	-4.245*** (.073)
Persuasive cues × brand type	-.181***(.007)	-.067*** (.008)
Informative cues × brand type	-.115***(.007)	-.060*** (.008)
Brand popularity × brand type	.125***(.024)	.105*** (.033)
Brand reputation × brand type	.065***(.015)	.136*** (.018)
Left-censored observations	28984	
Pseudo R^2	0.11	0.098

Notes: standard error in parentheses; * p<0.1,** p<0.05, *** p<0.01

Table 3: The results of 2SLS estimation

Persuasive cues	.024***	
Informative cues	-.046***	
Brand popularity	.502***	
Brand reputation	.182***	
Brand type	.226**	
Tweet length	.001***	
Photo	.051***	
Video	.763***	
Link	-.361***	
Log fans	.163***	
Grade	.003***	
Constant	-5.795***	
Persuasive cues × brand type	-.172***	
Informative cues × brand type	-.108***	
Brand popularity × brand type	.232***	
Brand reputation × brand type	.051***	
R-squared	28.83%	
First-stage regression		
F-statistics (p value)	1361.89 (0.000)	
Minimum eigenvalue statistic	1361.89	
Stock and Yogo's critical statistic	5% maximal IV relative bias	13.91
	10% maximal IV relative bias	9.08
	20% maximal IV relative bias	6.46
	30% maximal IV relative bias	5.39
Over identification test	Sargan (score) chi2(2) = 0.14022 (p = 0.7801)	
	Basmann chi2(2) = 0.1776 (p = 0.7254)	
Tests of endogeneity	Durbin (score) chi2(1) = 16.9437 (p = 0.0790)	
	Wu-Hausman F(1,159280) = 16.9437 (p = 0.0370)	

Notes: * p<0.1,** p<0.05, *** p<0.01; weak instrument concern is eliminated because the Cragg-Donald Wald F statistic is greater than 10 and minimum eigenvalue statistic is higher than Stock and Yogo's critical value [Stock & Yogo 2005]. Over identification tests are all not significant, indicating that there are no over-identification issues of our instruments, and our instruments are valid. Finally, the Durbin-Wu-Hausman test suggests that all p values are significant rejecting the null hypothesis, there is an endogenous issue. Brand value rank brand quality and related links.