Electronic Commerce Research and Applications 34 (2019) 100815

Contents lists available at ScienceDirect

Electronic Commerce Research and Applications

journal homepage: www.elsevier.com/locate/elerap

The magic of *danmaku*: A social interaction perspective of gift sending on live streaming platforms

Jilei Zhou[a], Jing Zhou[b,*], Ying Ding[c], Hansheng Wang[a]

[a] Guanghua School of Management, Peking University, 5 Yiheyuan Road, Haidian District, Beijing, China
[b] School of Statistics, Renmin University of China, No. 59, Zhongguancun Street, Haidian District, Beijing, China
[c] Renmin Business School, Renmin University of China, No. 59 Zhongguancun Street, Haidian District, Beijing, China

A R T I C L E I N F O

Keywords:
Live streaming
Paid gifting
Danmaku
Social interaction
Arousal theory

A B S T R A C T

A novel function of live streaming is that viewers can send paid gifts to broadcasters. In addition, viewers can engage with broadcasters by sending *danmaku*, a type of comment scrolled across the screen in real time. This paper investigates the role of viewers' social interaction in paid gifting on live streaming platforms. We argue that viewer-viewer interaction can prompt paid gifting by affecting viewers' arousal level through stimuli extracted from *danmaku*. Types of *danmaku*-related stimuli are presence of others, social competition, and emotional stimuli. Specifically, presence of others is measured by total number of words; social competition by debate level; and emotional stimuli by similarity of *danmaku*, number of excitement-related words, and number of emoji. Using data from a major live streaming platform in China, empirical results show that except for number of emoji, the other four variables positively affect paid gifting.

1. Introduction

In the past few years, live streaming has become a new social medium where broadcasters can deliver real-time broadcasts to viewers via the Internet. This is largely due to the fast development of the Internet and the massive adoption of mobile devices. In a live streaming platform, every broadcaster has a personal homepage called a channel. When a broadcaster is broadcasting in her channel, viewers are free to join in and exit at any time point. During the broadcast, they can engage with the broadcaster and other viewers by sending *danmaku*, a type of comment that is scrolled across the screen in real time. In addition, viewers can send "likes" and virtual gifts to broadcasters. It is worth noting that virtual gifts are bought from the live streaming platform with real money. Fig. 1 shows a typical live streaming channel on DOUYU.COM (*wwww.douyu.com*), which is one of the most famous live streaming platforms in China[1].

Live streaming has attracted numerous users in China. According to a public report, the number of live streaming users in China was about 310 million in 2016 and is expected to reach 495 million in 2019[2]. The burgeoning live streaming industry also leads to the inflow of capital. It is reported that in the year 2016, more than 25 financing events for live streaming took place in China, leading to a total investment over $2.8 billion[3]. For instance, the financing received by DOUYU.COM amounted to $300 million in 2016[4]. Like many Internet companies, live streaming firms rely on advertising as a common monetization strategy. Particularly in the US market, advertising is a major way for mainstream live streaming platforms to make profits. For example, advertisements through Facebook's live streaming service accounted for $3.3 billion of its total revenue in the first quarter of 2015[5]. However, Chinese live streaming firms derive only a small proportion of their revenue from advertising. Most of their revenue comes from a practice called paid gifting, which was invented by Chinese companies.

Paid gifting has been widely adopted by Chinese live streaming firms. Taking DOUYU.COM as an example (see Fig. 2a), viewers can reward broadcasters by sending different types of paid gifts while watching live streaming videos. These gifts are bought with real money ranging from 0.1RMB to 500RMB. Once a viewer sends gifts, her nickname and gift information (i.e., type and quantity) are displayed on

* Corresponding author.
E-mail address: zhoujing_89@126.com (J. Zhou).

[1] http://www.enet.com.cn/article/2017/0405/A20170405029810.html
[2] http://www.iimedia.cn/52067.html
[3] http://www.zhaihehe.com/?/news_detail/762
[4] http://www.sohu.com/a/143550373_757761
[5] https://www.smartinsights.com/digital-marketing-platforms/video-marketing/monetize-live-streaming/

https://doi.org/10.1016/j.elerap.2018.11.002
Received 8 March 2018; Received in revised form 26 October 2018; Accepted 19 November 2018
Available online 20 November 2018
1567-4223/

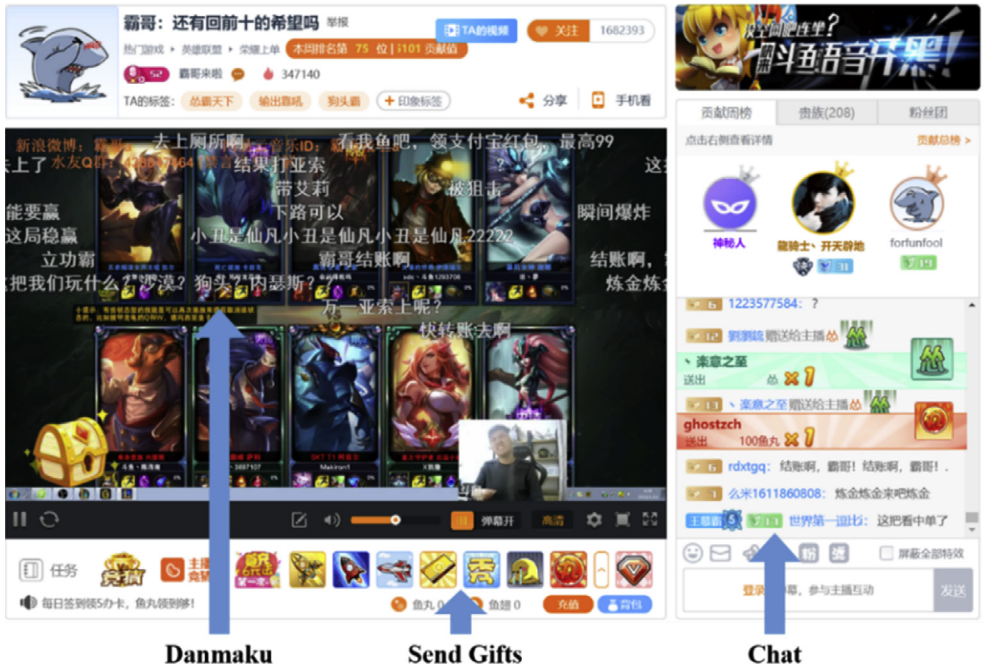
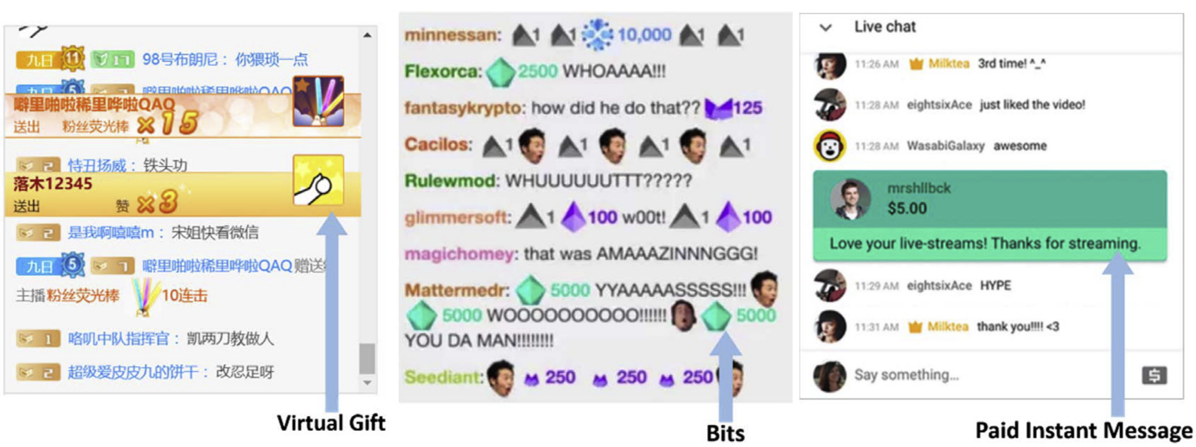


Fig. 1. A Channel Page on DOUYU.COM.



(a) DOUYU.COM (b) Twitch (c) YouTube Live

Fig. 2. Snapshots of Tipping on Live Streaming Platforms

the screen, and all viewers in the same channel can see it. Recently, several live streaming platforms in the US market also introduced this function, which allows users to donate to broadcasters. For example, Twitch announced a gifting system called *Cheering*, through which viewers can purchase "bits" and send them to their favorite broadcasters (see Fig. 2b). Similarly, viewers on YouTube Live are allowed to purchase paid instant messages to reward broadcasters (see Fig. 2c).

The business model relying on such paid gifting has become the main source of revenue for Chinese live streaming firms. For example, YY.COM, one of the most well-known live streaming sites in China, received $230 million in revenue from paid gifting in the fourth quarter of 2015[6]. Momo, another famous live streaming platform in China, has about 1.3 million paid users, who contributed $57.9 million revenue in the second quarter of 2016[7]. Although paid gifting is fairly new to Western markets, some firms in the US are already starting to generate revenue from it[8]. Since paid gifting affects the revenue of a firm, understanding the factors that affect paid gifting on live streaming platforms becomes important for practitioners.

While many studies have investigated the factors that impact gifting in the real world (Baskin et al., 2014; Belk, 1976; Gino and Flynn, 2011; Waldfogel, 1993; Yang and Urminsky, 2015; Zhang and Epley, 2012), investigation of the influence of paid gifting in the virtual community, especially in live steaming, has just begun. Status seeking is a popular explanation for paid gifting in virtual communities (Chen et al., 2017; Goode et al., 2014; Lampel and Bhalla, 2007; Toubia and Stephen, 2013). According to the status seeking framework, users send paid gifts to gain social-image related utility. Recently, the rapid growth of live

[6] http://technode.com/2016/05/05/virtual-gifts-are-still-the-top-earner-in-chinas-live-video-streaming-market/

[7] http://technode.com/2016/08/24/mobile-revenue-is-exceeding-pc-in-chinas-live-streaming-market/

[8] https://www.theguardian.com/money/2017/oct/07/millennials-making-a-living-from-livestreaming

streaming platforms has significantly facilitated social interaction activities. In this paper, we aim to examine the impact of social interaction on paid gifting rather than status seeking. The social interaction in broadcast media can be simply classified into two categories: broadcaster-viewer interaction and viewer-viewer interaction. We notice that a few researchers have already shown interest in examining the relationship between broadcaster-viewer interaction and viewers' support or consumption behavior in live streaming platforms (Chen et al., 2017; Hamari and Sjöblom, 2017; Payne et al., 2017). However, little is known about the role of viewer-viewer interaction.

In this work, we argue that viewer-viewer interaction can play an important role in prompting paid gifting by affecting viewers' arousal level. In the context of live streaming, *danmaku* is a major way for viewers to interact with others. We then claim that arousal level can be influenced by different stimuli extracted from *danmaku*. We focus on three types of *danmaku*-related stimuli: presence of others, social competition, and emotional stimuli. Specifically, the presence of others is measured by total number of words. Social competition is measured by debate level. Emotional stimuli are measured by the level of similarity of *danmaku*, number of excitement-related words, and number of emoji. According to arousal theory, we argue that viewer-viewer interaction is positively related to the amount of paid gifting because of elevated arousal level.

Data used in this paper were collected by crawling DOUYU.COM from September 1 to 17, 2017. The original dataset contained millions of observations that were identified by time to the second. Empirical results suggest that the proposed measurements for viewer-viewer interaction do have effects on paid gifting. Regarding presence of others, the more words viewers send, the more paid gifts they send. For social competition, a higher debate level between viewers leads to a higher intention to send paid gifts. For emotional stimuli, viewers are more likely to send gifts with a higher similarity level of *danmaku* and a higher number of excitement-related words. However, the number of emoji does not have a significant effect on paid gifting.

Compared to previous literature, we have made four contributions in this paper. First, we contribute to the literature on social media by investigating paid gifting in live streaming. While live streaming is an emerging social medium that differs in several ways from traditional social media, investigation into this emerging social media is just beginning (Payne et al., 2017; Sjöblom and Hamari, 2017). A popular function in live streaming is sending paid gifts, which is quite rare in more traditional social media, and there are few studies on live streaming that focus on paid gifts. Our study is among the first studies to investigate paid gifting in live streaming. Second, we contribute to the theory on gifting by considering paid gifting in a virtual community from a social interaction perspective. Prior studies showed that gifting in the virtual world correlates highly with status seeking (Chen et al., 2017; Goode et al., 2014; Lampel and Bhalla, 2007; Toubia and Stephen, 2013). However, in this paper, we show that social interaction is another important feature affecting paid gifting in social media. Third, we contribute to the literature on broadcast media consumption by considering interaction between viewers. Prior literature on broadcast media consumption has paid much attention to investigating the role of broadcaster-viewer interaction. This research found that broadcaster-viewer interaction can positively affect supporting behavior (Payne et al., 2017), watching frequency (Sjöblom and Hamari, 2017), and paid gifting (Chen et al., 2017). However, little is known about the effect of viewer-viewer interaction, which is another important social interaction in the live streaming platform. Fourth, this research relies on large-scale data crawling from a famous live streaming platform in China. Unlike lab experiments or survey questionnaires in previous studies, we collected complete data, including gifting and second-by-second chatting records along with other general information. This method provides richer user information and more accurate model results.

The rest of the article is organized as follows. In Section 2, we review relevant literature on gifting theory, social interaction, and arousal theory. We then propose the main hypotheses that we aim to test in Section 3. Next, we introduce the methodology in Section 4, including the data collection process and variable construction. Descriptive analysis and empirical results are shown in Section 5. In conclusion, theoretical implications, managerial implications, and future studies are summarized in Section 6.

2. Theoretical review

In this section, we review the theoretical underpinnings of our research by first providing an overview of gifting theory both in the real word and the virtual community. Then we focus on the relationship between social interaction and paid gifting based on an arousal framework.

2.1. The impact factors of gifting

This paper is related to three streams of literature. The first is the literature on gifting. The factors that influence gifting in the real world have been widely studied in many fields such as economics, sociology, and anthropology. Prior studies reveal that altruism is one of the most popular explanations for gifting. For example, many researchers point out that sending a gift is a strategy to maximize a recipient's economic utility (Baskin et al., 2014; Gino and Flynn, 2011; Waldfogel, 1993; Zhang and Epley, 2012). Such a utility maximization framework boosts the development of theoretical models in real-word gifting. Instead of increasing a recipient's economic welfare, Yang and Urminsky (2015) suggested that gifting is positively associated with a desire to induce recipients' positive reaction, such as making them happy or smile. In addition to altruism, traditional gifting theories also highlight the role of exchange and reciprocity between rewarders and recipients. For example, Belk (1976) identified four functions for gifting: they are communication, social exchange, economic exchange, and socialization. Among them, Belk (1976) highlighted the importance of exchange. Based on Belk (1976)'s study, Sherry (1983) proposed a model of the gift exchange process that included social, personal, and economic dimensions.

While previous literature mainly focused on gifting in the real world, recently a few researchers have begun to show interest in studying the factors that impact sending gifts in virtual communities and social media. Status seeking has been proven to be the major factor that affects virtual gifting. It consists of activities aiming to improve an actor's image-related utility in a group, which is judged by the degree of prestige, honor, or deference (Lampel and Bhalla, 2007). For instance, Toubia and Stephen (2013) found that image-related utility is a significant factor to motivate users to contribute contents in social media. Lampel and Bhalla (2007) suggested that image-related utility plays an important role in gift giving in virtual consumer communities. However, the studies mentioned above mainly focus on digital materials, which are not paid for with money. Only recently has research on paid gifting begun. Goode et al. (2014) found strong evidence that paid gifting is associated with future enhancements of rewarders' social status. In the context of live streaming especially, Chen et al. (2017) found that increasing audience size improves viewers' image-related utility and thus paid gifting.

2.2. The effect of social interaction and arousal theory

The second stream of literature relates to social interaction theory, which has been popularly adopted in prior studies to explain social behavior. Social interaction refers to "an interpersonal action or a relationship between self and others" (Varey, 2008), which may contain exchange, competition, cooperation, conflict, or coercion (Gqffman, 1983). Social interaction is a fundamental need for human beings. Driven by belongingness, people have a significant tendency to form interpersonal relationships (Baumeister and Leary, 1995). It has been acknowledged that social interaction with others can affect not only innovation or new adoption behavior (Rogers, 2010; Ryan and Gross, 1943) but also quitting behavior, such as dimission (Castilla, 2005) or customer churn (Nitzan and Libai, 2011). The rapid growth of social media has facilitated social interaction activities. A survey conducted by Shriver et al. (2013) showed that a significant portion of people report that the motivation to tweet is to facilitate socializing or interacting with others. McAlexander et al. (2002) found that consumers who join a brand community have a higher level of engagement with firm products and brands. Live streaming is a typical social medium, where viewers can interact with each other. This social interaction may affect viewers' paid gifting.

Social interaction on broadcast media can be separated into two categories: broadcaster-viewer interaction and viewer-viewer interaction. Broadcaster-viewer interaction refers to the interaction between one broadcaster and many viewers. Viewer-viewer interaction, which is also called peer interaction, refers to the interaction among a group of viewers. Some literature focuses on the relationship between broadcaster and viewer from the perspective of how the relationship affects viewers positively. For example, Payne et al. (2017) showed that in Twitch, interaction between instructors and viewers is positively related to viewers' learning performance. Hamari and Sjöblom (2017) found that the attractiveness viewers perceived in eSports players is positively associated with eSports watching frequency. Moreover, they showed that social interaction, such as cheering for favorite players, also positively affects viewers' eSports watching frequency. Chen et al. (2017) proposed that viewers in a crowded channel have a lower chance to win attention from the broadcaster and therefore have less incentive to send gifts. Prior literature has paid much attention to investigating the effect of broadcaster-viewer interaction, while little is known about viewer-viewer interaction in paid gifting. We then attempt to fill in this gap with this study.

We argue that viewer-viewer interaction can play an important role in prompting paid gifting by affecting viewers' arousal level. Arousal is defined as a motivational state ranging from a continuum of drowsiness to extreme wakefulness (Berlyne, 1966; Duffy, 1962). An individual's state of arousal can be influenced by a variety of sensory stimuli, such as color, ambient sounds, and alcohol or caffeine consumption (Batra and Ghoshal, 2017). The more intense the stimuli are, the higher the arousal level is. In the context of live streaming, the interaction between viewers can be seen as sensory stimuli. A more active interaction indicates high-intense stimuli, which intuitively induces a high level of arousal. Such high arousal level at a given point can impair a calm, careful decision-making process, which usually results in hedonic purchase behavior (Fedorikhin and Patrick, 2010) or overbidding in auction (Ku et al., 2005). The paid gifting in a live streaming platform can be seen as a hedonic product. Therefore, we suggest that viewer-viewer interaction can increase arousal level, which can prompt paid gifting.

3. Hypotheses development

Danmaku is one of the major ways for interaction between viewers in a live streaming platform. Specifically, viewers can interact with each other by sending *danmaku* simultaneously to either chat or debate with other viewers. As a result, viewer-viewer interaction can be detected by text mining of *danmaku*. There are three types of *danmaku* stimuli that can affect arousal level: the presence of others, social competition, and emotional stimuli.

3.1. Impact of presence of others on paid gifting

The presence of others has long been known to directly affect arousal level. Zajonc (1965) first proposed a drive-arousal model in the social facilitation literature, describing the arousal-enhancing effect of the presence of others. Other empirical research found that the presence of others can enhance an actor's arousal level (Borden et al., 1976; Elliot and Cohen, 1981; McKinney et al., 1983; Mullen et al., 1997; Ukezono et al., 2015). It is worth noting that there are many types of "others," such as audience, co-actors, and so on (Zajonc, 1965). Specifically, audience refers to people who are not engaged with the participant but are explicitly present to observe the participant's behavior (Borden et al., 1976) while co-actors refer to people who are engaged in the same behavior as the participant (Amoroso and Walters, 1969). In our context, for each specific viewer, other viewers are regarded as co-actors. Such co-actors can create a stressful environment in which co-actors are likely to "require a readiness to accommodate interactions, stimulate periodic social monitoring, engender apprehension about being evaluated, or generate attentional conflict" (Mullen et al., 1997). Therefore, the presence of co-actors is arousal-increasing. In this study, we use the total number of words contained in *danmaku* to reflect the presence of others. Intuitively, the larger the total number of words is, the stronger the perception of the presence of others is, and the higher the arousal level is. This will induce paid gifting. Therefore, we have the following hypothesis:

Hypothesis 1. The number of gifts given by viewers in a period is positively related to the total number of words in the same period.

3.2. Impact of social competition on paid gifting

Previous research also found that individuals will experience higher arousal level under more intense social competition. For instance, studies on Internet auctions have shown that competitive interaction can induce a state of competitive arousal between bidders, which will affect bids (Adam et al., 2015; Ku et al., 2005). Exposure to competitive sports materials can also increase arousal level and then increase the likelihood of subsequent aggressive behavior (Branscombe and Wann, 1992). Moreover, the arousal level is likely to be higher when the provocation is clearly attributed to an identifiable opponent (Zillmann and Bryant, 1974). In this study, we use debate level to measure social competition between viewers. Debate refers to a condition in which viewers take opposite views about certain events, such as a broadcaster's performance. Therefore, the provocation evoked by debate can be clearly attributed to an identifiable opponent, which will increase arousal level. According to the competition-arousal framework, when viewers are involved in a heated discussion, they tend to experience high arousal level and then are likely to send gifts. Therefore, we have the following hypothesis:

Hypothesis 2. The number of gifts given by viewers in a period is positively related to the level of debate in the same period.

3.3. Impact of emotional stimuli on paid gifting

Emotional stimuli are stimuli charged by various emotions, such as happiness, fear, and excitement. Sanbonmatsu and Kardes (1988) claimed that emotionally charged stimuli, such as fear-arousing ads, political statements, or religious messages, can affect individuals' physiological arousal. Morrow et al. (1981) also found that emotionally charged sentences produced a greater number of responses than neutral sentences. The association between emotional stimuli and arousal is not limited to adults, and even infants can exhibit arousal in response to others' emotional expressions (Upshaw et al., 2015) as when newborns hearing another infant cry will be aroused and cry as well (Dondi et al., 1999). For viewer-viewer interaction in live streaming platforms, we consider three typical measures of emotional stimuli: similarity level of *danmaku*, number of excitement-related words, and number of emoji. First, viewers tend to express appreciation to a broadcaster by sending similar compliments simultaneously if a live stream is attractive. Such similar appreciation-related emotional stimuli can increase viewers' arousal level and then affect their gifting. Second, viewers often use exclamation marks or *666* in *danmaku* to express excitement and admiration to a broadcaster. Here, *666* is a popular cyberword meaning "excellent" that is usually used by viewers to praise broadcasters. In this paper, the number of excitement-related words is summarized by counting exclamation marks and the cyberword *666*. The more excitement words there are, the more emotional stimuli the viewers are exposed to, which may subsequently lead to gifting. Finally, along the same lines, the number of emoji contained in *danmaku* is the third typical emotional stimulus that may facilitate gifting intention by enhancing arousal level. These considerations lead to the following three hypotheses:

Hypothesis 3. The number of gifts given by viewers in a period is positively related to the similarity level of *danmaku* in the same period.

Hypothesis 4. The number of gifts given by viewers in a period is positively related to the number of excitement related words in the same period.

Hypothesis 5. The number of gifts given by viewers in a period is positively related to the number of emoji in the same period.

4. Data and variable construction

4.1. Data description

Data used in this study were collected by crawling DOUYU.COM, which is one of the most famous live streaming platforms in China. DOUYU was founded in 2014 and focuses on broadcasting such content as computer games, ACG (animation, comics, and games), singing, daily life, and other recreational activities. There are two reasons why we chose DOUYU.COM as a representative of live streaming platforms. First, with the most active users, DOUYU.COM is one of the top live streaming platforms in China[9]. It was reported that DOUYU had approximately 100 million registered users and 15 million daily active users in 2017[10]. Second, paid gifting was originally invented by Chinese companies. Users in China are familiar and happy with the paid gifting function, and paid gifting contributes a large amount of revenue to firms. To meet the needs of this research, we collected two kinds of data. One is general information about each channel including channel ID and its corresponding category. This information is immutable across time. The other kind of data is the time-varying behavior of viewers per second in each channel, such as entering, sending *danmaku,* and sending gifts. Recordings of *danmaku* in all live streaming sessions were derived from web crawling.

Data were collected from September 1, 2017, to September 16, 2017. To offer a basic description of the data, we summarize data from September 2, 2017, as an illustration[11]. There were 2130 unique channels and about 1.7 million unique users on the DOUYU platform on that day. We show the changing pattern in the number of viewers and gifts throughout the 24 h of the day. From Fig. 3(a) we can see that the number of viewers reached the lowest point at 5 a.m. and then gradually increased. The first peak was at about noon and then viewership decreased thereafter. The second peak was at midnight. In contrast, the number of gifts revealed a different trend, as shown in Fig. 3(b). Although the number of gifts reached its low point at 5 a.m., viewers preferred to send gifts at night rather than in the afternoon. The peak of gifting occurred around 10p.m.

Next, we summarize the types of live videos that were broadcast on the platform. There were a total of 86 categories of live videos in DOUYU.COM, including computer games, entertainment, outdoor activities, and so on. For simplicity, we chose to show the top 10 most popular types[12] of channels, ranked by number of viewers and number of channels respectively (See Table 1). By number of viewers we mean the ranking is based on total number of viewers entering, which reflects popularity among viewers. By number of channels we mean the ranking is based on the channel types that attract the most broadcasters. As we can see, almost half of the types were related to computer games. This indicates that live computer games are a dominant part of DOUYU.COM. However, there is a discrepancy between the two types of results based on different ranking rules. Although most broadcasters tend to broadcast a PC Game named League of Legends, channels broadcasting ACG attract the most viewers.

4.2. Variable construction

In this section, we construct variables through text mining from *danmaku*. The original data were collected from web crawling DOUYU.COM per second, and the amount of data used for analysis was over one hundred million. In order to reduce the sample size, we aggregated the original data at the minute level. For the dependent variable of gift sending, we measured it by the number of gifts that were received by broadcasters every minute. Then the independent variables were also constructed at the minute level. Since all the *danmaku* were written in Chinese form, we adopted the jiebaR software package to do word segmentation.

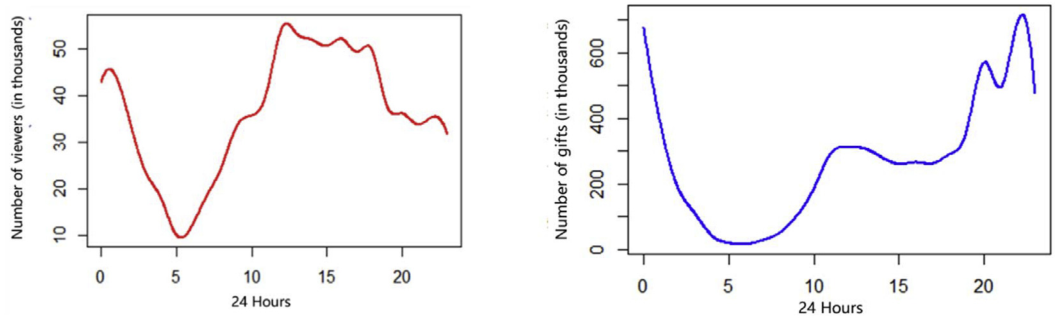
(1) Total number of words. First, we divided each piece of *danmaku* into separate words. Then all the words were filtered by a stop word list (e.g. "the," "is," "at"). In this way, only meaningful words were kept. We then calculated the total number of words by counting the number of meaningful words every minute.
(2) Level of debate. Debate is a situation in which viewers take opposing views and argue with each other. That is to say, when debate occurs, the number of positive and negative words in *danmaku* are generally the same. So in our case, the level of debate measures the absolute value of difference between positive and negative words every minute. In order to identify the valence (positive, negative, or neutral) of a word, we adopted the text segmentation technique. First, we used a comprehensive dictionary code, called sentiment lexicon, to infer whether a word was positive or negative. Then after all words were marked with a valence, we calculated the absolute difference between positive and negative words every minute. Lastly, we divided this value by the total number of words in the same period. Fig. 4 shows the steps in a more detailed way. As we can see, the lower the value is, the higher the level of debate is. In order to reflect intuitive thinking, we defined the level of debate as the opposite number of the value calculated earlier.
(3) Similarity level of *danmaku*. This level was defined as the number of unique words divided by the total number of meaningful words every minute. As we can see, the lower the value is, the higher the similarity level of *danmaku* is. In order to reflect intuitive thinking, we subtracted the above value from 1 to identify the similarity level of *danmaku*.
(4) Proportion of excitement-related words. This variable is calculated as the sum of exclamation marks and cyberword *666's* contained in *danmaku* divided by the total number of meaningful words every minute.
(5) Proportion of emoji. An emoji is a special symbol that is used to express the mood of viewers. The proportion of emoji was calculated as the number of emoji divided by the total number of

[9] https://www.scmp.com/tech/enterprises/article/2124662/chinas-booming-live-streaming-industry-may-have-reached-its-peak

[10] https://medium.com/tripleuniverse/esports-streaming-is-china-ahead-of-us-f73ea5a89b30

[11] Data analyses were also conducted on the other days. The results are consistent for all days, which shows the representativeness.

[12] These channels are not selected for analysis, just to describe the live video situation in this platform.



(a) Number of Viewers (b) Number of Gifts

Fig. 3. Different Trends during a 24-Hour Day

Table 1
Top 10 Types of Channels.

By Number of Viewers		By Number of Channels	
Category	Proportion	Category	Proportion
ACG	16.16%	League of Legends	13.57%
League of Legends	10.56%	PUBG	11.31%
Outdoors	9.97%	King of Glory	11.08%
PUBG	6.80%	ACG	6.95%
Beauty	5.55%	Beauty	6.71%
Console Game	4.52%	Outdoors	4.13%
Automobile	4.06%	Console Game	3.57%
King of Glory	3.90%	DNF	3.52%
Digital Technology	3.41%	Digital Technology	1.92%
Film &TV	3.31%	Hearthstone	1.88%

PUBG stands for Player Unknown's Battlegrounds.

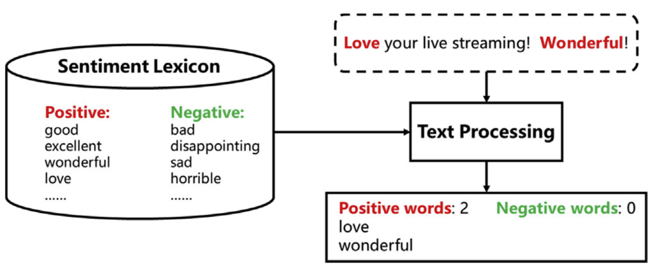


Fig. 4. Lexicon-Based Sentiment Analysis

meaningful words every minute.

In addition to the above five independent variables, we also controlled for potentially confounding factors, such as time effect (e.g., 00:00–01:00 or 19:00–20:00) and day-of-the-week effect (e.g., Sunday or Monday). Moreover, we also controlled for variables that reflect the momentum effect and competition effect. We used the last number of viewers entered and last number of gifts gained to measure the momentum effect. The competition effect was derived from the last number of viewers left and the last number of gifts lost.

(6) Last number of viewers entered. We determined the number of viewers who entered a broadcasting channel in the last minute.
(7) Last number of viewers left. Since leaving behavior was hidden in our data, we used other channels' last number of viewers entered to approximate the number of viewers left. The approximation is based on the premise that viewers are more likely to switch between the same type of channels. For any two channels, we assumed that the more overlap between viewers, the more likely it was to switch between them. Therefore, we constructed an overlap ratio-based matrix. Each element in this matrix was the overlap ratio between any two channels. Specifically, viewers in each channel could be abstracted into a vector, and the overlap ratio could be calculated using the angle cosine value between two vectors (See Fig. 5). This matrix was used to quantify the influence from other channels by assigning different weights to the viewer size. Then the last number of viewers left was calculated by multiplying this ratio-based matrix by the number of viewers entered in other channels in the last minute.

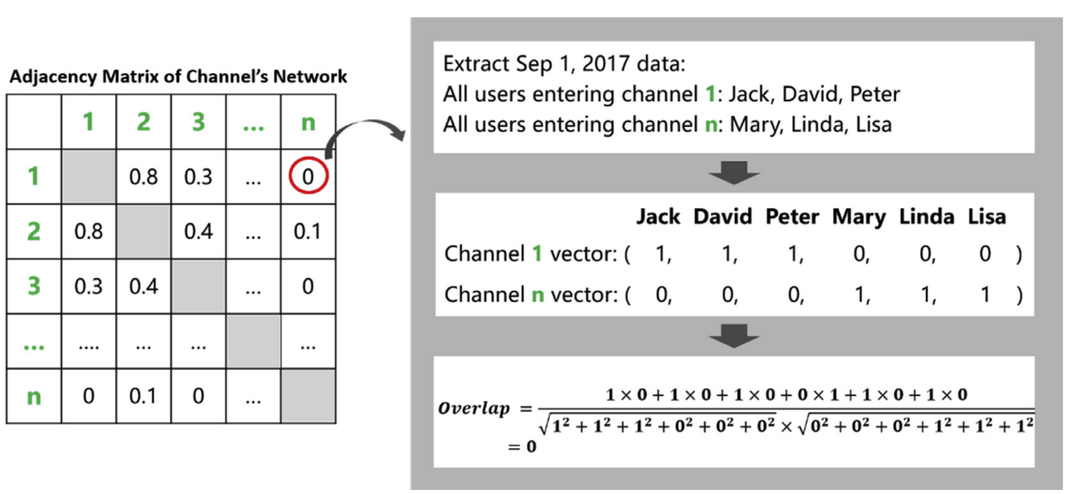


Fig. 5. Similarity-Based Network between Channels

(8) Last number of gifts gained. This was computed as the number of gifts sent by viewers in a broadcasting channel in the last minute.
(9) Last number of gifts lost. As with the last number of viewers left, this variable cannot be observed directly. Following similar steps in constructing the last number of viewers left, we multiplied the ratio-based matrix by the number of gifts gained in other channels in the last minute to calculate the last number of gifts lost.

5. Empirical results

5.1. Descriptive analysis

According to previous analyses, computer games are one of the dominant live broadcasting videos in DOUYU.COM. For the purpose of illustration, we conducted analysis on channels that broadcast King of Glory, which was one of the most famous battle games in 2017,[13] and the results were robust. The original data were aggregated at the minute level, and the shortest time for live broadcasting was restricted to no less than ten minutes. As a result, our final data for model analysis included 317,309 observations.

Table 2 shows the descriptive statistics of key variables for the unbalanced panel with 672 channels across 317,309 observations. From the table we can see that the average number of viewers entering into a live channel per minute is 1.17, while each broadcaster on average receives 17.88 gifts per minute. This result indicates that gifting behavior in live streaming is not as rare as we may think. We further find that viewers in live streaming are fond of using excitement symbols such as "!," the cyberword *666*, and emoji when chatting with each other. The maximum number for these variables was much larger than for the other variables. As shown in the last column of the table listing the summary statistics, we found that the variability for the total number of words and last number of gifts gained was much larger than for the other variables. In the next subsection, we show the empirical results.

5.2. Model results

To examine the hypotheses proposed earlier, we conducted a linear regression. Empirical results are reported in Table 3. The proposed model is statistically significant ($F = 14520$) and suitable (adjusted $R^2 = 66.46\%$). This large R^2 indicates that the proposed independent variables explain much of the gifting behavior. According to the results of the VIF test, there is no multiple collinearity issue.

We find several interesting results that are new and different from previous studies. First, Table 3 reports a significant positive effect for the total number of words ($\beta = 0.009$, $p < 0.001$). This means that the higher the number of total words is, the more gifts a broadcaster will receive. Second, the level of debate also has a significant positive ($\beta = 4.083$, $p < 0.001$) relationship with the dependent variable. That is to say, a heated discussion will lead to a higher tendency to send gifts. Therefore, hypotheses 1 and 2 are supported. Next, the similarity of *danmaku* ($\beta = 28.659$, $p < 0.001$) and the number of excitement-related words ($\beta = 3.237$, $p < 0.001$) also have a positive effect on gift sending. These variables measure the interaction between viewers and broadcasters. Therefore, hypotheses 3 and 4 are supported. However, the number of emoji ($\beta = -0.056$, $p = 0.152$) shows no significant effect on gifting. Hypothesis 5 is not supported. This is because in this case we can only extract emoji symbols from *danmaku*, but cannot know whether each is positive or negative. Therefore, the effect of emoji may not be detected. We summarize our hypotheses testing results in Table 4.

In addition to the main hypotheses, we also derived several other findings from control variables, most of which are lagged terms. First, we obtain a significant positive effect for the lag term of number of viewers entered ($\beta = 2.312$, $p < 0.001$). This result implies the role of status seeking, which is consistent with prior studies of virtual gifting. The larger the number of entered viewers is, the higher level of status-based utility they derive from their peers. Second, we also find a significant positive effect for the lag term of number of gifts gained ($\beta = 0.751$, $p < 0.001$). This reflects a herding effect, which is also widely discussed in prior studies (Banerjee, 1992; Chen, 2008; Hwang and Salmon, 2004). Finally, the lag term of number of viewers left ($\beta = -3.871$, $p = 0.036$) and number of gifts lost ($\beta = -0.772$, $p < 0.001$) are negatively associated with gift sending. This indicates that different channels have a competitive relationship. Having a large number of viewers left shows that a live channel is no longer popular, leading to a decline in gift sending.

Table 2
Descriptive Statistics.

Variable	Min	Median	Mean	Max	SD
Total number of words	0.000	10.000	45.840	34,543	334.906
Level of debate	−1.000	−0.010	−0.060	0.000	0.123
Similarity of *danmaku*	0.000	0.070	0.130	1.000	0.172
Number of excitement-related words	0.000	0.000	0.191	532.300	2.535
Number of emoji	0.000	0.125	0.564	3368.750	17.715
Last number of viewers entered	0.000	0.000	1.177	115.000	2.639
Last number of viewers left	0.000	0.010	0.030	6.410	0.084
Last number of gifts gained	0.000	0.000	17.880	9094.000	115.933
Last number of gifts lost	0.000	0.001	0.004	168.000	1.889

Table 3
Results of Linear Regression.

Variable	Parameter	Std.error	P value	VIF
Constant	1.863.	0.975	0.056	
Total number of words	0.009***	0.0004	< 0.001	1.147
Level of debate	4.083***	1.029	< 0.001	1.026
Similarity of danmaku	28.659***	2.156	< 0.001	1.277
Number of excitement-related words	3.237***	0.521	< 0.001	1.217
Number of emoji	−0.056	0.007	0.152	1.163
Last number of viewers entered	2.312***	0.366	< 0.001	1.487
Last number of viewers left	−3.871*	1.844	0.036	1.343
Last number of gifts gained	0.751***	0.025	< 0.001	1.425
Last number of gifts lost	−0.772***	0.103	< 0.001	1.351
Time period	-included-			
Week	-included-			

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 4
Hypotheses Testing Results.

Hypothesis		Support
H1	Total number of words↑, gifts number↑	Supported
H2	Level of debate↑, gifts number↑	Supported
H3	Similarity of *danmaku*↑, gifts number↑	Supported
H4	Number of excitement-related words↑, gifts number↑	Supported
H5	Number of emoji↑, gifts number↑	Not Supported

6. Discussion and implication

6.1. Detailed discussion about empirical results

In this paper, we study the impact of viewer-viewer interaction on paid gifting in live streaming. We focus on three types of viewer-viewer interaction in various scenarios; they are presence of others, social

[13] We also analyzed data of other game live videos (e.g., PlayerUnknown's Battlegrounds, League of Legends).

competition, and emotional stimuli. To measure and estimate the effect of different types of viewer-viewer interaction, we construct a set of variables from *danmaku* using text mining techniques. Specifically, we use total number of words and debate level to measure the presence of others and social competition respectively. For emotional stimuli, we propose three measurements: similarity level of *danmaku*, number of excitement-related words, and number of emoji.

An empirical study was conducted using data collected from crawling one of the biggest live streaming platforms in China. We found several interesting results. *First*, the presence of others, which is measured by total number of words, has a positive effect on paid gifting. Based on arousal theory, the presence of others can affect arousal level directly (Amoroso and Walters, 1969; Borden et al., 1976; Zajonc, 1965). In the live streaming context, the larger the total number of words is, the stronger the perception of the presence of others is, and the higher the arousal level is. This situation will facilitate paid gifting.

Second, social competition has a positive effect in the sense that a stronger debate level attracts more viewers to send gifts. In a debate situation, viewers often take different views about a broadcaster's performance, and their provocation is clearly attributed to an identifiable opponent. Therefore, such competitive interaction will induce a state of competitive arousal between viewers and then increase the likelihood of paid gifting (Zillmann and Bryant, 1974).

Third, for different emotional stimuli, we find that the higher the similarity level of *danmaku* is and the higher the number of excitement-related words is, the easier it is for viewers to send gifts. However, the number of emoji shows no significant effect on gifting. This is an interesting result. We speculate that perhaps emotional valence is part of the explanation (Lane et al., 1999; Paradiso et al., 1999). When viewers want to express praise to broadcasters, they tend to send similar compliments or exclamation marks simultaneously in *danmaku*. That is to say, the similarity of *danmaku* and the number of excitement-related words are praise-related emotional stimuli. People who are aroused by such positive emotional stimuli are more likely to make a hedonic purchase (e.g., gifting in live streaming platforms) than those aroused by negative emotional stimuli (Beatty and Ferrell, 1998; Chang et al., 2011; Verhagen and van Dolen, 2011). However, in our case, we couldn't tell the valence of emoji symbols. As a result, their effect on paid gifting may not have been detected.

Finally, we also determined several findings from control variables, most of which are lagged terms. For example, the lag number of viewers entered has a positive effect on paid gifting, while the lag number of viewers left has a negative effect. These results are consistent with previous studies that focus on status seeking.

6.2. Theoretical implications

This paper has several theoretical implications compared with previous literature. First of all, we contribute to the literature on social media by investigating live streaming, which is an emerging social medium equipped with a novel function called paid gifting. Previous literature on social media mainly focuses on traditional social media platforms, such as Facebook, Twitter, and Wikipedia. However, live streaming has several characteristics that differ from those of traditional social media. For example, users in live streaming platforms can engage more deeply through real-time interactions with broadcasters. In addition, paid gifting is a novel function, which is quite rare in traditional social media. Although recently a few researchers began to show interest in investigating user behavior in the live streaming platform (Payne et al., 2017; Sjöblom and Hamari, 2017), very few of them focus on paid gifts. Our study is among the first studies to investigate paid gifting in live streaming.

Second, we contribute to the literature on gifting by considering paid gifting on live streaming platforms. Previous literature mainly focuses on gifting in the real world. It shows that altruism (Baskin et al., 2014; Gino and Flynn, 2011; Zhang and Epley, 2012) and reciprocity (Belk, 1976; Sherry, 1983) are two key factors that influence real-world gifting. Although recently a few researchers began to show interest in sending gifts in virtual communities and social media, most of them mainly focus on free gifts (e.g., digital media), which are not paid for with money (Lampel and Bhalla, 2007; Toubia and Stephen, 2013). In the meantime, many researchers find gifting in the virtual world is highly correlated with status seeking (Chen et al., 2017; Goode et al., 2014; Lampel and Bhalla, 2007; Toubia and Stephen, 2013). However, social interaction is also an important feature in virtual communities, which has proved to have a great effect on many social behaviors in social media (Baumeister and Leary, 1995; Nitzan and Libai, 2011; Rogers, 2010; Shriver et al., 2013). Our study fills the gap by focusing on the effect of social interaction on paid gifting in the virtual world.

Third, we contribute to the literature on broadcast media consumption by considering interaction between viewers. Some studies explain viewers' support or consumption behavior in broadcast media from a broadcaster-viewer interactive perspective (Chen et al., 2017; Payne et al., 2017; Sjöblom and Hamari, 2017), while little is known about the effect of viewer-viewer interaction on viewers' support or consumption behavior in broadcast media, especially paid gifting behavior. To this end, in a novel departure from the existing literature, we determine the effect of viewer-viewer interaction on paid gifting.

6.3. Managerial implications

On the one hand, this study gives the live streaming platform insight into designing *danmaku* exposure. For example, engineers can highlight the debate content or excitement-related words in *danmaku* to enhance viewers' arousal level. This will further induce paid gifting. On the other hand, our findings also give broadcasters an insight on how to receive more gifts when broadcasting. Specifically, they should focus on not only broadcaster-viewer interaction but also viewer-viewer interaction. Accordingly, they can develop marketing strategies that aim to improve interaction or communication among viewers. For example, one of the most popular events in live streaming is the online game Player Killing, which features intense competition between different channels.

6.4. Limitations and future research

To the best of our knowledge, we are among the first few studies to investigate the factors influencing paid gifting in live streaming from a social interaction perspective. Several limitations can serve as avenues for future research. For example, the data used in this study were collected from crawling only one live streaming platform in China. Recently, several live streaming platforms in the US market also introduced paid gifting function. One interesting question is whether the effect of social interaction on paid gifting will be moderated by cultural difference, such as collectivism in China and individualism in the US. Studying this question could enhance our theoretical contribution to the literature in social media. In addition, in this study, we extract only five kinds of interaction scenarios between viewers. Future research could expand this study by considering other levels of interaction and activities for viewers in varied scenarios. Third, the results of this study mainly focus on the correlation between impact factors of social interaction and paid gifting. A future study could employ a lab experiment to investigate the motivation at the micro level, which may contribute to the literature on the psychological mechanism of paid gifting. Forth, the empirical findings suggest that number of emoji has no significant effect on gifting. This may due to the insufficient information provided by emoji. Therefore, a natural extension of the current research is to collect more detailed data about emoji. As live streaming becomes more and more popular, we hope this research will stimulate more important topics to be studied in this industry.

Acknowledgements

Zhou's research is supported in part by National Natural Science Foundation of China (Grant No. 71702185), Fund for Building World-class Universities (disciplines) of Renmin University of China and Center for Applied Statistics of Renmin University of China. Ding's research is supported in part by National Natural Science Foundation of China (Grant No. 71502172). Wang's research is supported in part by National Natural Science Foundation of China (Grant Nos. 71532001, 11525101, 71332006). It is also supported in part by China's National Key Research Special Program (Grant No. 2016YFC0207704).

References

Adam, M.T., Krämer, J., Müller, M.B., 2015. Auction fever! How time pressure and social competition affect bidders' arousal and bids in retail auctions. J. Retail. 91, 468–485.
Amoroso, D.M., Walters, R.H., 1969. Effects of anxiety and socially mediated anxiety reduction on paired-associate learning. J. Pers. Soc. Psychol. 11, 388.
Banerjee, A.V., 1992. A simple model of herd behavior. Q. J. Econ. 107, 797–817.
Baskin, E., Wakslak, C.J., Trope, Y., Novemsky, N., 2014. Why feasibility matters more to gift receivers than to givers: a construal-level approach to gift giving. J. Consum. Res. 41, 169–182.
Batra, R.K., Ghoshal, T., 2017. Fill up your senses: a theory of self-worth restoration through high-intensity sensory consumption. J. Consum. Res. 44, 916–938.
Baumeister, R.F., Leary, M.R., 1995. The need to belong: desire for interpersonal attachments as a fundamental human motivation. Psychol. Bull. 117, 497.
Beatty, S.E., Ferrell, M.E., 1998. Impulse buying: modeling its precursors. J. Retail. 74, 169–191.
Belk, R.W., 1976. It's the thought that counts: a signed digraph analysis of gift-giving. J. Consum. Res. 3, 155–162.
Berlyne, D.E., 1966. Conflict and arousal. Sci. Am. 215, 82–87.
Borden, R.J., Hendrick, C., Walker, J.W., 1976. Affective, physiological, and attitudinal consequences of audience presence. Bull. Psychon. Soc. 7, 33–36.
Branscombe, N.R., Wann, D.L., 1992. Physiological arousal and reactions to outgroup members during competitions that implicate an important social identity. Aggres. Behav. 18, 85–93.
Castilla, E.J., 2005. Social networks and employee performance in a call center. Am. J. Sociol. 110, 1243–1283.
Chang, H.-J., Eckman, M., Yan, R.-N., 2011. Application of the Stimulus-Organism-Response model to the retail environment: the role of hedonic motivation in impulse buying behavior. Int. Rev. Retail Distrib. Consum. Res. 21.
Chen, Y.-F., 2008. Herd behavior in purchasing books online. Comput. Hum. Behav. 24, 1977–1992.
Chen, Y., Lu, S., Yao, D., 2017. The Impact of Audience Size on Viewer Engagement in Live Streaming: Evidence from A Field Experiment. Working Paper.
Dondi, M., Simion, F., Caltran, G., 1999. Can newborns discriminate between their own cry and the cry of another newborn infant? Dev. Psychol. 35, 418.
Duffy, E., 1962. Activation and Behavior. Wiley, New York.
Elliot, E.S., Cohen, J.L., 1981. Social facilitation effects via interpersonal distance. J. Soc. Psychol. 114, 237–249.
Fedorikhin, A., Patrick, V.M., 2010. Positive mood and resistance to temptation: the interfering influence of elevated arousal. J. Consum. Res. 37, 698–711.
Gino, F., Flynn, F.J., 2011. Give them what they want: the benefits of explicitness in gift exchange. J. Exp. Soc. Psychol. 47, 915–922.
Goode, S., Shailer, G., Wilson, M., Jankowski, J., 2014. Gifting and status in virtual worlds. J. Manage. Inform. Syst. 31, 171–210.
Gqffman, E., 1983. The interaction order. Am. Sociol. Rev. 48, 1–17.
Hamari, J., Sjöblom, M., 2017. What is eSports and why do people watch it? Internet Res. 27, 211–232.
Hwang, S., Salmon, M., 2004. Market stress and herding. J. Empirical Finance 11, 585–616.
Ku, G., Malhotra, D., Murnighan, J.K., 2005. Towards a competitive arousal model of decision-making: a study of auction fever in live and Internet auctions. Organ. Behav. Hum. Decis. Process. 96, 89–103.
Lampel, J., Bhalla, A., 2007. The role of status seeking in online communities: giving the gift of experience. J. Comput.-Mediat. Commun. 12, 434–455.
Lane, R.D., Chua, P.M., Dolan, R.J., 1999. Common effects of emotional valence, arousal and attention on neural activation during visual processing of pictures. Neuropsychologia 37, 989–997.
McAlexander, J.H., Schouten, J.W., Koenig, H.F., 2002. Building brand community. J. Market. 66, 38–54.
McKinney, M.E., Gatchel, R.J., Paulus, P.B., 1983. The effects of audience size on high and low speech-anxious subjects during an actual speaking task. Basic Appl. Soc. Psychol. 4, 73–87.
Morrow, L., Vrtunski, P.B., Kim, Y., Boller, F., 1981. Arousal responses to emotional stimuli and laterality of lesion. Neuropsychologia 19, 65–71.
Mullen, B., Bryant, B., Driskell, J.E., 1997. Presence of others and arousal: an integration. In: Group Dynamics: Theory, Research, and Practice, pp. 52.
Nitzan, I., Libai, B., 2011. Social effects on customer retention. J. Market. 75, 24–38.
Paradiso, S., Johnson, D.L., Andreasen, N.C., O'Leary, D.S., Watkins, G.L., Boles Ponto, L.L., Hichwa, R.D., 1999. Cerebral blood flow changes associated with attribution of emotional valence to pleasant, unpleasant, and neutral visual stimuli in a PET study of normal subjects. Am. J. Psychiatry 156, 1618–1629.
Payne, K., Keith, M.J., Schuetzler, R.M., Giboney, J.S., 2017. Examining the learning effects of live streaming video game instruction over Twitch. Comput. Hum. Behav. 77, 95–109.
Rogers, E.M., 2010. Diffusion of Innovations. Simon and Schuster.
Ryan, B., Gross, N.C., 1943. The diffusion of hybrid seed corn in two Iowa communities. Rural Sociol. 8, 15.
Sanbonmatsu, D.M., Kardes, F.R., 1988. The effects of physiological arousal on information processing and persuasion. J. Consum. Res. 15, 379–385.
Sherry Jr, J.F., 1983. Gift giving in anthropological perspective. J. Consum. Res. 10, 157–168.
Shriver, S.K., Nair, H.S., Hofstetter, R., 2013. Social ties and user-generated content: evidence from an online social network. Manage. Sci. 59, 1425–1443.
Sjöblom, M., Hamari, J., 2017. Why do people watch others play video games? An empirical study on the motivations of Twitch users. Comput. Hum. Behav. 75, 985–996.
Toubia, O., Stephen, A.T., 2013. Intrinsic vs. image-related utility in social media: why do people contribute content to twitter? Market. Sci. 32, 368–392.
Ukezono, M., Nakashima, S.F., Sudo, R., Yamazaki, A., Takano, Y., 2015. The combination of perception of other individuals and exogenous manipulation of arousal enhances social facilitation as an aftereffect: re-examination of Zajonc's drive theory. Front. Psychol. 6, 601.
Upshaw, M.B., Kaiser, C.R., Sommerville, J.A., 2015. Parents' empathic perspective taking and altruistic behavior predicts infants' arousal to others' emotions. Front. Psychol. 6, 360.
Varey, R.J., 2008. Marketing as an interaction system. Aust. Market. J. (AMJ) 16, 79–94.
Verhagen, T., van Dolen, W., 2011. The influence of online store beliefs on consumer online impulse buying: a model and empirical application. Inform. Manage. 48, 320–327.
Waldfogel, J., 1993. The deadweight loss of Christmas. Am. Econ. Rev. 83, 1328–1336.
Yang, A., Urminsky, O., 2015. Smile-seeking Givers and Value-seeking Recipients: Why Gift Choices and Recipient Preferences Diverge. Working Paper.
Zajonc, R.B., 1965. Social facilitation. Science 149, 269–274.
Zhang, Y., Epley, N., 2012. Exaggerated, mispredicted, and misplaced: when "it's the thought that counts" in gift exchanges. J. Exp. Psychol. Gen. 141, 667.
Zillmann, D., Bryant, J., 1974. Effect of residual excitation on the emotional response to provocation and delayed aggressive behavior. J. Pers. Soc. Psychol. 30, 782.