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# Discovery of behavioral patterns in online social commerce practice

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**Abstract**

Discovery of behavioral patterns in online social commerce practice becomes important in this digital era. In this article, we propose a systematic approach to behavioral pattern discovery, and apply it in an emerging online social commerce venue: live streaming. We investigate behavioral patterns in gifting encouragement in live streaming to understand online social commerce practice. Our proposed approach is based on multiple triangulation, including data source triangulation (i.e., streamers, viewers, and actual behavior) and data collection method triangulation (i.e., interviews, focus groups, and observations). Through multiple triangulation, four behavioral patterns of gifting encouragement are discovered: (i) requesting a certain gift for providing a particular service, (ii) creating a raffle, (iii) eliciting competition between individuals, and (iv) eliciting competition between groups. This research reveals the special behavioral patterns in live streaming, and thus increases our knowledge of social commerce practices. This research provides a systematic approach to discover online behavioral patterns, and provides practical implications in live streaming platforms, especially in marketing and platform design.

This article is categorized under:

Application Areas > Business and Industry

**KEYWORDS**

behavioral patterns, multiple data sources, triangulation

## 1 | INTRODUCTION

Data analysis is useful to discover hidden behavioral patterns and predict behavior (Pahwa, Taruna, & Kasliwal, 2017). It has been widely applied in online behavior studies, such as customers' economic behavior (Balan & Rege, 2017; Pahwa et al., 2017), social interactions (Barbier, Tang, & Liu, 2011; Ortigosa, Carro, & Quiroga, 2014; Tabassum, Pereira, Fernandes, & Gama, 2018), gaming behavior (Ahmad & Srivastava, 2014) and educational behavior (Desai, Ramasamy, & Kiper, 2021; He, 2013). Recently, with the popularity of live streaming, analyzing data to uncover behavior patterns in this new digital environment has become an important research area (He, 2013; Zhu, Yang, & Dai, 2017).

Live (video) streaming is an emerging form of social commerce that has become popular globally and attracted large numbers of viewers. It allows viewers to watch a streamer broadcast an activity online and participate in real-time. During a live stream, viewers can interact with the streamer or other viewers by text or emoji. The streamer can provide "interactive performances" (Jia, Wang, Liu, & Xie, 2020), and give audio (e.g., talking to viewers) or visual (e.g., body movements) responses to viewers. It makes live streaming a new place for social interaction (Hamilton, Garretson, & Kerne, 2014). Crucially, viewers can voluntarily send streamers digital gifts (also known as virtual gifts) at any time during a live stream. The digital gifts can be purchased using real currency from live streaming platforms. Streamers and their streaming host platforms share the revenue from digital gifts received as an important source of income (iResearch, 2018). In effect, streamers strive to encourage viewers to gift more. This appears to be a novel form of social commerce characterized by "taking advantage of relationships in a social network to gain commercial benefits" (Liang, Ho, Li, & Turban, 2011, p. 73), and has not yet received much research attention.

We intend to investigate streamers' behavioral patterns of gifting encouragement in live streaming to understand this special social commerce, as gifting encouragement is the most important social commerce activity in live streaming. Since the Chinese live streaming industry has been the largest in terms of the number of online users and profit made (Restream, 2020). We intend to use the Chinese live streaming industry as an example in this study.

In this research, we propose a systematic approach to discover behavioral patterns in online social commerce. As previous qualitative studies on behavior investigation only involving a single data source or method, have been widely challenged due to low reliability and validity (Decrop, 1999). We use an innovative systematic approach, multiple triangulation (Thurmond, 2001), which combines data source triangulation and data collection method triangulation to investigate online behavioral patterns. In our approach, data are drawn from three data sources, including verbal self-report from both streamers and viewers, and the online behaviors of streamers and viewers observed from the investigators. Data coming from different standpoints supplement each other to obtain convergent and divergent conclusions. Accordingly, three methods of data collection are applied, including interviews, focus groups and observations.

Through multiple triangulation, we ensure that the "social" side of e-commerce is examined from both creator and audience perspectives in live streaming, and that verbal claims about gifting practices are backed up with observations of practice.

## 2 | BACKGROUND

### 2.1 | Social commerce

Social commerce is a relatively new e-commerce paradigm. Its basic feature is that enterprises leverage social relationships to facilitate online product-selling or service-selling (Liang et al., 2011). It is rooted in the development of Web 2.0 technologies and social media (Lin, Li, & Wang, 2017) and has transformed e-commerce into a more socialized and interactive way of doing business (Curty & Zhang, 2013). Compared with ordinary e-commerce, social commerce involves more social elements (Liang et al., 2011).

The practices of social commerce have been evolving over time (Curty & Zhang, 2011) with the advent and growth of new technology, platforms, algorithms (Chen, Wang, Zhang, Wang, & Xu, 2019; Guo, Yi, Wang, Ye, & Zhao, 2014; Wang, Gao, Shi, & Wang, 2016; Yu, Gao, Wang, & Wang, 2018; Yu, Jung, Kim, & Jung, 2018) and social media tools. The social commerce venues have evolved from originally text-oriented blogs, social networking sites (SNSs) (Wang & Zhang, 2012) and social shopping websites, to today's most popular live streaming which combines text, image, audio, and video, and provides live interactions.

Although live streaming has opened up a new era of social commerce, to date only limited studies on social commerce have been conducted in the context of live streaming. Unlike other social commerce websites such as Amazon and Taobao, social commerce in live streaming is a special category since most of the streamers there do not focus on product-selling, but provide interactive performance (Jia et al., 2020) and rely on voluntary gifting from viewers to make profits. This relationship-based social commerce is obviously different from the product-based social commerce explored before. Hence, there is a need to understand this special social commerce practice.

### 2.2 | Gifting behavior in live streaming

Several gifting behavioral patterns have been identified by previous research in live streaming. From a macro-perspective, viewers' gifting behavior is found to be correlated with the number of viewers (Zhu et al., 2017). The more viewers, the more gifts are likely to be received (Zhu et al., 2017). Also, most viewers tend to purchase cheap gifts, while a small number of viewers contribute the more valuable gifts, critical to overall revenue (Tu, Yan, Yan, Ding, & Sun, 2018; Zhu et al., 2017). Moreover, most viewers just gift to one or two streamers, and the most valuable gifts are normally given to the most popular streamers (Tu et al., 2018). Most gifting behaviors were found to be synchronous with a barrage of comments or text communication (Tu et al., 2018).

From the micro-perspective, viewers' engagement positively affects their gifting behavior (Yu, Gao, et al., 2018; Yu, Jung, et al., 2018). Engagement includes but is not limited to the amount of stream watching time, closeness to the streamers and users' dependence on live streaming. Stream-watching time is also found to positively influence gifting behavior (Zhu et al., 2017). Moreover, viewers' gifting behavior is stimulated by other viewers on the same channel (Tu et al., 2018; Zhu et al., 2017). In other words, viewers are more likely to gift when they see others gift.

Viewers with gifting behavior are found to be regular users (Gros, Wanner, Hackenholt, Zawadzki, & Knautz, 2017). Some viewers are even found to fight to be the top gift-senders (Sjöblom, Törhönen, Hamari, & Macey, 2017). Viewers with such behaviors are found to easily develop a deeper relationship with the streamers, and affect the content of streams (Lu, Xia, Heo, & Wigdor, 2018).

Gender differences in actual gifting behavior have not been investigated. However, gender differences are found in viewers' decision to gift. Women's decisions on gifting are based on their financial situations, while men make their gifting decisions based on their interactions with the streamer (Lee, Yen, Wang, & Fu, 2019).

Most studies on gifting are explored from the viewers' perspective, except one conducted from streamers' perspective with the investigation of gifting behavior between streamers. Findings show that when a streamer gives gifts to other streamers, other streamers tend to gift the streamer back (Tu et al., 2018). This process forms a reciprocal gifting relationship between streamers. Nevertheless, there is a lack of a general gifting study from the streamers' perspective, which motivates us to conduct our study.

### 2.3 | Triangulation

Most qualitative approaches, especially those that investigate a behavioral pattern only through interviews, are often criticized for their biases and low reliability (Decrop, 1999). It has been accepted that triangulation can serve as a strategy to mitigate these disadvantages through the convergence and agreement of information derived from different theories, investigators, sources and methods (Flick, 2004).

Triangulation is a method, which investigates a phenomenon by combining at least two theories, methods, data sources or investigators in one single study (Thurmond, 2001). A study adopting more than one type of triangulation is described as multiple triangulation. Although triangulation is an effective method, extant triangulation studies are few, and most of them are from nursing literature (Carter, Bryant-Lukosius, DiCenso, Blythe, & Neville, 2014; Thurmond, 2001). Moreover, most current related studies focus on providing a theoretical description of triangulation rather than applying it as a method in the research. Overall, it seems triangulation has not received much attention and has not been used much as a method in the literature. This leads to a thought if we could apply triangulation in discovering streamers' behavioral patterns of gifting encouragement in our study.

## 3 | METHODS

### 3.1 | Data source triangulation and data collection method triangulation

In our study, we use both data source triangulation and data collection method triangulation to understand how streamers encourage online gifting. Our data source triangulation draws information from streamers' perspectives, and two more independent data sources, including viewers' perspectives and observations of actual online behavior. When integrating information from different data sources, it is likely to obtain new and valuable knowledge (Wang et al., 2018). Triangulating these perspectives helps to supplement and verify streamers' accounts of their own strategies. Viewers, especially regular viewers, are a group who know the streamers well in terms of their online behaviors. Viewers can also provide their motivations for their own gifting, which can help us to better understand why streamers' commercial behaviors work. Finally, online behavior observations allow verification that these subjective accounts are actually practiced.

Based on the characteristics of each data source, a between-method triangulation is designed, involving three contrasting research methods: individual interviews, focus group interviews, and online observations. Interviewing is a flexible and the most direct way to interact with participants (Rubin & Rubin, 2012), and it allows exploration of participants' attitudes, opinions, and perceptions based on over-arching research questions (Barriball & While, 1994). Using interviews helps to gather in-depth information, and allows clarification when necessary. Thus, we use interviews to obtain information from streamers.

Focus groups enable researchers to collect more information in a relatively shorter period than with one-on-one interviews (Lederman, 1990). They allow the dynamic exchange of attitudes and opinions between individuals (Bohnsack, 2004). This synergy of interactions enables participants to react to comments from others, and generate more ideas or controversy through discussion (Bohnsack, 2004). Thus, we use focus groups to gather data from viewers.

The verbal data collected from interviews and focus groups are through self-report, and therefore are quite subjective. Systematic observations can balance out these subjective biases by triangulating their operation in real-time with more objectively coded observations of online behavior (Flick, 2004). Thus, in this research, we use observations to gain objective online behaviors.

Triangulation of these three data collection methods can make use of strengths from each method, balance out their weaknesses, and increase reliability and validity (Carter et al., 2014). Our multiple triangulation model is shown in Figure 1.

## 3.2 | Participants and procedures of data collection

### 3.2.1 | Data collected from individuals

*Participants*. Participants were 10 Chinese streamers (five men, five women) from six popular live streaming platforms, including Kuai, Inke, Xiongmao, Douyu, Xigua and Huya. Ages were from 20 to 49 with an average of 27.6 years old. They were all popular streamers with at least 130,000 online followers at the time of interviews. According to iResearch (iResearch, 2018), only 1.4% of game streamers had over 20,000 followers as of December 2017. Also, a stream drawing over 1000 viewers was considered to be massive (Hamilton et al., 2014). In our study, all the participants reported that each of their streams in the previous 3 months drew over 5000 viewers. Hence, all the interviewed streamers were popular in terms of the total number of followers and the number of viewers drawn in each stream. The details of the interviewed streamers are shown in Table 1.

*Procedures*. These streamers were recruited through the Bulletin Board System (BBS), SNSs, and snowball sampling. They were selected according to criterion-based and purposive sampling strategies (Ritchie, Lewis, & Elam, 2003). According to data released, about 70% of the streamers were born in or after the Year 1990 (Xinhuanet, 2018), and streamers of talent shows (singing, dancing, cooking, talk shows, etc.) were found to attract more gifts than game-play streamers (Jinriwanghong, 2017). Hence, we chose more streamers born in or after the Year 1990, and involved more talent shows streamers than game-play streamers in our study.

The interviews took place online from October 28, 2018 to January 21, 2019 with a 40 min average duration. Streamers participated voluntarily. Semi-structured interviews were carried out following a basic research

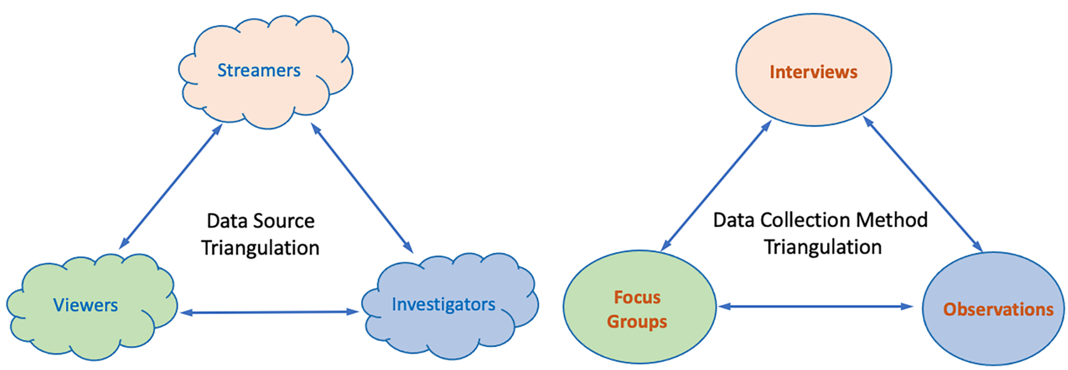


FIGURE 1 Multiple triangulation model

TABLE 1 Details of streamersgroups

| No. | Gender | Contents | Age | No. of followers | Platforms |
|---|---|---|---|---|---|
| S1 | Male | Talk show | 20 | 651,904 | Kuai |
| S2 | Female | Instrument playing | 27 | 503,682 | Inke |
| S3 | Male | Singing | 49 | 517,056 | Kuai |
| S4 | Female | Dancing | 22 | 524,387 | Xiongmao |
| S5 | Male | Game-play | 28 | 253,799 | Douyu |
| S6 | Male | Appearance/physical attractiveness | 27 | 188,215 | Douyu |
| S7 | Female | Instrument playing, teaching and instruments selling | 22 | 134,671 | Xigua |
| S8 | Female | Eating | 25 | 241,020 | Huya |
| S9 | Female | Anime culture | 21 | 276,572 | Xiongmao |
| S10 | Male | Outdoor activities | 32 | 323,453 | Xiongmao |

TABLE 2 Details of focus groups

| Group no. | No. of participants | Coded no. | Average age | Gender |
|---|---|---|---|---|
| G1 | 8 | A1-A8 | 21.4 | 2 female, 6 male |
| G2 | 8 | A9-A16 | 18.5 | 1 female, 7 male |
| G3 | 7 | A17-A23 | 18.9 | 2 female, 5 male |

question “without considering the content and genre of your streams, how do you encourage viewers to gift more in the streams?”

All interviews were transcribed. Any identifying information of the streamers was deleted. The transcripts were coded and clustered according to themes using thematic analysis (Clarke & Braun, 2017). To ensure the transcripts were translated equivalently, the Brislin back-translation model (Brislin, 1970) was used. In detail, the first bilingual translator independently translated the Chinese transcripts into an English version. Then the second bilingual translator independently back-translated the English version into a Chinese version, which was used to compare with the original Chinese transcripts. When errors are found, the translation process will be iterated by the third and fourth bilingual translators until the contents were equivalent in their meaning.

### 3.2.2 | Data collected from the focus groups

*Participants*. Participants were 23 regular viewers (18 men, five women). Ages ranged from 18 to 32, with an average age of 21.2. They were from different places in China, and included students and workers/professionals. All reported that they watched popular live streams, across a wide range of genres. Also, all the participants confirmed that, in the last 3 months before focus group interviews, they (i) spent more than CNY6/USD0.89 in gifting and (ii) had at least 10 gifting experiences.

Normally, two to three focus groups are enough to obtain over 80% of themes, while three to six focus groups could capture 90% of the themes (Guest, Namey, & McKenna, 2017). Hence, we allocated the participants into three focus groups. Details of the focus groups are shown in Table 2.

*Procedures*. These viewers were recruited through BBS sites, and SNSs. More young viewers were chosen to reflect that nearly 70% of online viewers were under 30 years old (iResearch, 2018).

Focus groups took place from October 14, 2018 to November 3, 2018. The average duration of each group discussion was 60 min. All participants volunteered for the study. The focus groups were conducted based on the research question “under what circumstances, do you gift streamers and why?” The transcripts of group interviews were dealt with in the same way as stated in Section 3.2.1.

### 3.2.3 | Data collected via observations

*Participants*. Participants were 167 streamers (78 men, 89 women) chosen and observed from six of the most popular live streaming platforms (i.e., Xiongmao, Kuai, Douyu, Huya, Yizhibo, and YY) which provide comprehensive streams. Among 167 streamers, 113 are talent show streamers (48 men, 65 women), and 54 are game-play streamers (30 men, 24 women).

*Procedures*. The observed streamers were randomly chosen from the streamer hotlists from six live streaming platforms including the streamers interviewed. The duration of each observation time varied from 10 min to up to 3 h depending on the length of each stream from November 15, 2018 to March 15, 2019. Data from observations are descriptive and used to compare with data from the interviews and focus groups.

## 4 | DATA ANALYSIS AND BEHAVIORAL PATTERNS DISCOVERED

After analyzing the transcripts, initial behaviors for gifting encouragement were extracted from streamers' interviews through identifying the patterns of meaning (themes) by thematic analysis (Clarke & Braun, 2017). Then these initially identified behaviors for gifting encouragement were compared and triangulated with findings from focus groups and online observations. Through multiple triangulation, four convergent behavioral patterns of gifting encouragement were discovered. For each behavioral pattern, the information from different data sources is reported.

### 4.1 | Behavioral pattern 1: Request a certain gift for providing a particular service

*From the streamers*: To request a certain gift for an extra service from viewers was used to attract more gifts according to streamers. When viewers requested special performances (e.g., singing a song) or special roles (e.g., being the moderator) during a stream, streamers provided a price for their request. For example, streamers may request a digital gift costing CNY6/USD0.89 for singing a particular song. As to the special roles, the most popular one is to be a *moderator* (also known as *room manager)* who has the power to mute other viewers or kick them out of the channel. Some streamers disclosed that they normally asked for a (particular) digital gift from viewers before they granted the role (the moderator) to a viewer. For other streamers, although they did not directly provide a price for this role or other services, they were "*more likely to grant the role or provide services to generous viewers who had gifted more in their streams* (S8)".

*From the viewers*: Viewers expressed the view that to become a moderator is an incentive for them to gift. Other popular incentives include being selected into the streamer's fan group or to participate in activities organized by the streamers or platforms. Also, it seems that, sometimes, some viewers gifted the streamers not out of voluntariness, but because they wanted to get particular services, answers or feedback from the streamers.

*From the investigators*: After observing 167 streamers, we found 121 of them posted the exact gifts/prices of services in their channels; or they verbally mentioned the prices of services during their streams. Also, we observed that streamers encouraged gifting by adding viewers to their offline fan groups or appointing viewers to be the moderators. We found, on several occasions, that streamers did not mention the price for becoming a moderator, but they did appoint the viewers who had gifted high value of gifts to be their moderators.

### 4.2 | Behavioral pattern 2: Create a raffle for viewers

*From the streamers*: Streamers held the view that setting up raffles helped them receive more gifts. Streamers usually requested a particular gift before viewers get a chance to participate in a raffle. Streamers found "*lured by huge awards (e.g., iPhone or huge currency), most of the viewers would like to spend small and affordable money to buy the raffle ticket and try their luck*" (S5). Consequently, streamers could attract more digital gifts.

*From the viewers*. Viewers admitted that sometimes they gifted not because of the stream itself, but because they "*wanted to win the raffle*" (A1). Some viewers said that they would "*gift more if there are more raffles*" (A21). Apart from raffles, viewers mentioned more online prize-winning activities organized by streamers, such as online quizzes and electronic red-envelope fights (a game, where different amounts of lucky money are allocated randomly). Although the activities are different, they all require viewers to gift to some extent before they can participate in the game.

*From the investigators*: Prize-winning activities such as online quizzes and electronic red-envelope fights were observed. In total, 109 out of 167 streamers had this behavior. In our observations, the prices of the tickets to join the games varied across streamers. The awards also varied. Only a few raffles with big prizes (a rare example is shown in Figure 2) were observed. The popular awards included the role of the moderator, digital gifts and virtual currency. Of the platforms that supported the raffle function, almost half the streamers were found to conduct this activity (as shown in Figure 3).

## 4.3 | Behavioral pattern 3: Elicit competition between individual viewers

*From the streamers*: To create competitions between individual viewers was practiced by streamers to encourage gifting. Two different practices were identified: direct elicitation and indirect elicitation. Streamers usually take advantage of viewers' pursuit of top positions on the fame ranking lists. Viewer fame ranking lists rank gift senders' names based on the value of digital gifts they send to the streamer. These fame ranking lists can be seen by all who enter the channel. In the direct elicitation, streamers verbally lead a competition between two or more viewers. For example, the streamer says that "*Viewer B is going to surpass Viewer A to become the new No. 1 on the viewer fame list*" (S9). Subsequently, Viewer A might send more gifts to make sure to remain first on the list. On the other hand, Viewer B might send even more gifts to exceed Viewer A. In this situation, the streamer benefits from the competition between A and B. Interestingly, all the streamers who reported having this practice in the interviews were female. In the indirect elicitation, streamers "*award the viewer who ranks first on the fame ranking list with gifts or personal contact details*" (S4 & S8). Viewers compete for the awards, and streamers benefit from viewers' competition.

*From the viewers*: Viewers recognized that streamers elicit gifting competition between viewers, especially between super-fans and generous viewers. They said that if they came second in the fame list, they might send more gifts to become the first, especially "*when the gap between the first and the second is not huge*" (A9).

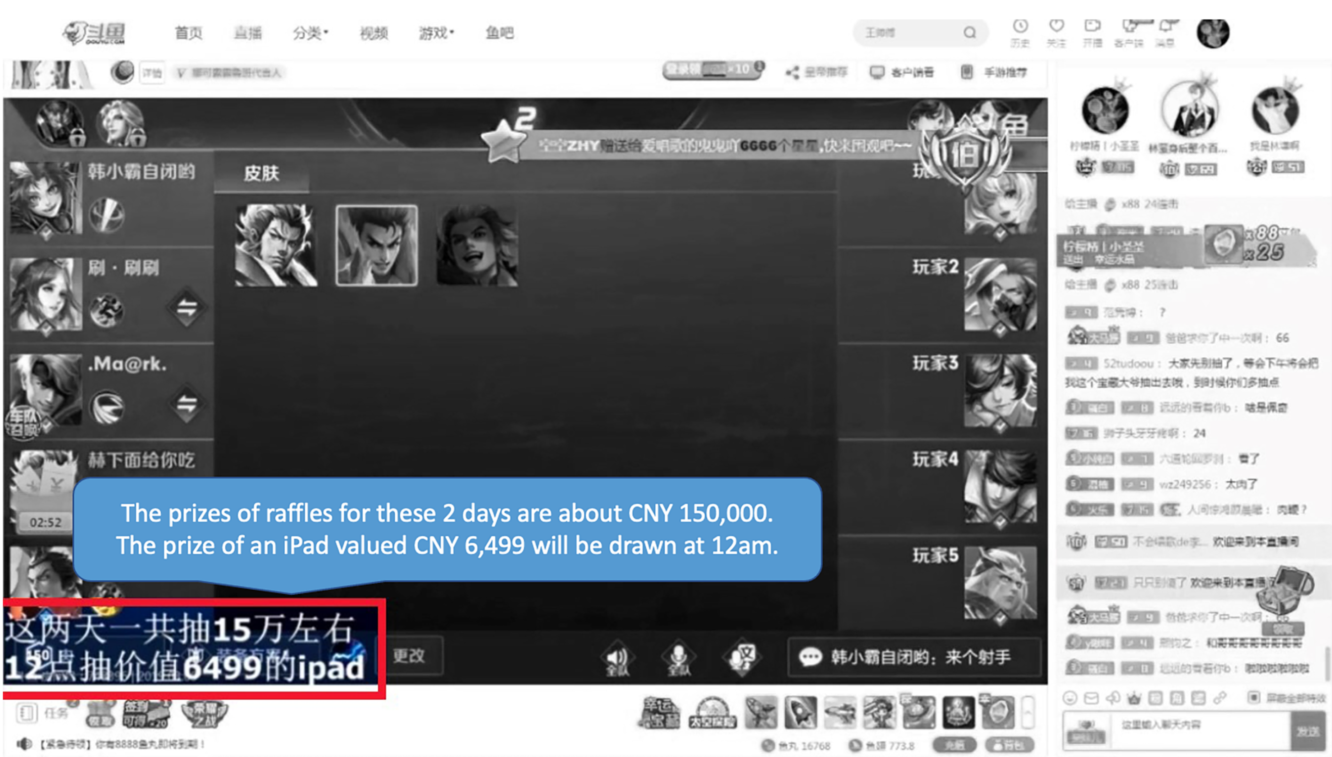


FIGURE 2 The screenshot of raffle with a big prize


**FIGURE 3** A moment when seven out of the 12 most popular streamers are using raffle

*From the investigators*: Direct elicitation of gifting competitions between viewers were not very common in our observations. Overall, only 7 out of 167 cases were observed. Also, all the 7 streamers who directly elicit competitions were female. In comparison, indirect competition elicitation was more common. Streamers were found to award the viewer who comes first on the fame list with real gifts, personal contact details, etc. 79 out of 167 streamers were observed to have this practice. Gender differences in using this technique were not observed.

## 4.4 | Behavioral pattern 4: Elicit competition between different viewer groups

*From the streamers*: According to streamers, creating a competition between groups is also a practice to encourage gifting. When competing (called PK/VS in streams) with other streamers, two streamers project themselves within a fixed period time. During this time, the values of the gifts received by the two streamers are shown vividly on screen as shown in Figure 4. The winner is the one who receives more total value of digital gifts during the fixed competition period. By eliciting competitions, streamers create more opportunities to make viewers excited about gifting, using the motivation of intergroup competition to encourage sending digital gifts.

*From the viewers*: Viewers mentioned that they liked to send more gifts to support their streamers when the streamers are in the PK/VS mode or other contests. Viewers said they "*did not want their streamers to lose in the competition*" (A19) so that they gifted more to fight for their streamer's winning. Some believed that they would "*buy and send more digital gifts unintentionally under the competitive atmosphere*" (A10).

*From the investigators*: In our observations, 93 out of 167 steamers were observed to use PK/VS. More talent show streamers were found to use PK/VS than game-play streamers. Figure 5 shows PK is widely used by talent show streamers. Also, streamers who knew one another (and were probably collaborating) were more frequently involved in PK/VS than strangers (i.e., genuine competition between streamers). Interestingly, streamers were noticed to deliberately verbally increase the intensity of the competition during PK/VS mode. For example, when Streamer A received more gifts, Streamer A would provoke the supporters of Streamer B by saying "*the fans in your channel are not giving strong support today*." This led the supporters of Streamer B to send more gifts to Streamer B. Then, viewers of Streamer A gifted more as well, to make sure their streamer would win. Thus, both streamers benefit from the intergroup competition.


FIGURE 4 The screenshot of PK

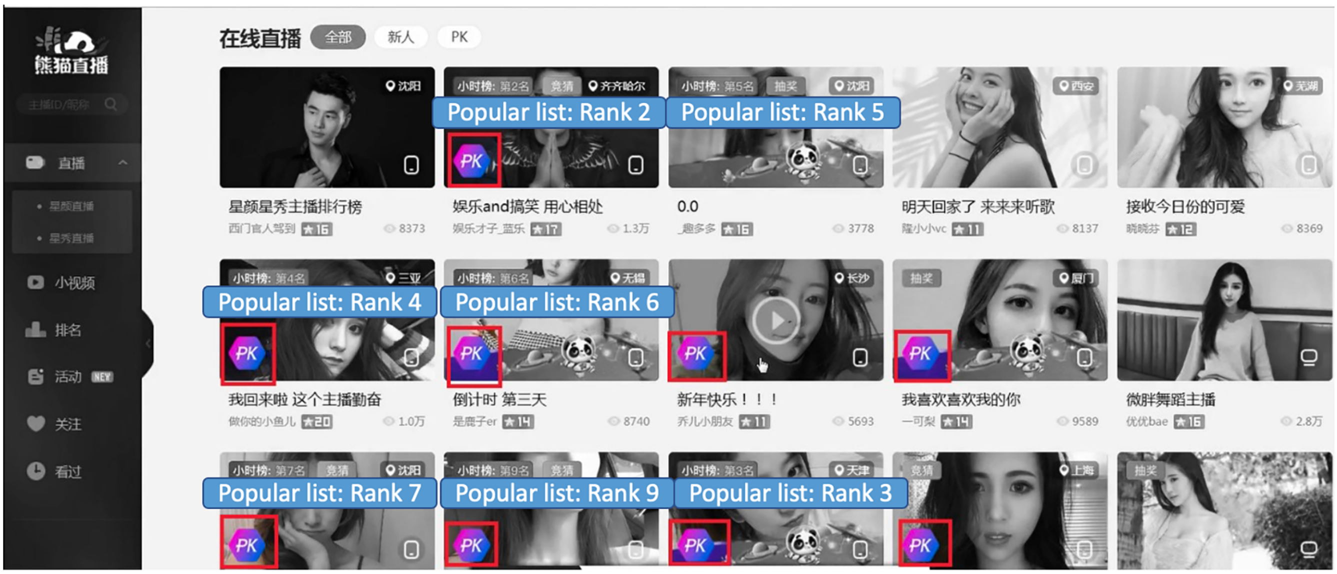


FIGURE 5 A moment when nine out of the 12 most popular streamers are in the PK mode (highlighted)

# 5 | DISCUSSION AND IMPLICATIONS

## 5.1 | General discussion

Our findings suggest that social commerce practices evolve with the development of IT. Advances in IT facilitate the emergence of new platforms and new functions. Compared with previous social commerce practices/venues, our findings indicate there are three differences between social commerce practice in live streaming and other previous social commerce practices. Firstly, the social commerce in live streaming includes more subjects (sellers). Apart from selling from enterprises as shown in previous research (Lin et al., 2017), in the live streaming context, selling can take place on an individual basis. Secondly, the social commerce in live streaming contains broader objects. In previous social commerce studies, objects to be sold are limited to products or services. As investigated and described in our study, interactions, attention, or virtual roles can now be used to get commercial benefits in the new social commerce practice. Thirdly, the social commerce in live streaming involves more interactions and communications. Live streaming platforms provide more new functions for live interactions and instant communications between sellers (streamers) and buyers (viewers). Sellers (streamers), therefore, can make use of the new functions (e.g., PK/VS modes) to conduct unique commercial interactions and communication to make profits. We therefore predict that there will be even more interactions involved in future social commerce practices.

Our study also illustrates viewers' gifting behaviors and motivations. Viewers appear to be actively involved in gifting to satisfy their inherent needs, such as the pursuit of power and attention, entertainment, interactions with people, and money/prizes winning. This is in accordance with the uses and gratifications theory (Ruggiero, 2000).

As far as we know, multiple triangulation is for the first time brought into behavior studies and is proved to be a useful and efficient method. Triangulation provides a comprehensive multi-perspective view, being used as "a validation strategy", "an approach to generalization of discoveries" and "a route to additional knowledge" (Flick, 2004, p. 183).

## 5.2 | Discussion of discovered behavioral patterns of gifting encouragement

Streamers were found to proactively request gifts before giving viewers benefits in Behavioral Pattern 1. This finding is new in the literature. Previous research only found that after gifting, viewers could get the opportunity for exclusive chats and receiving streamers' gratitude (Gros et al., 2017), develop a further relationship with the streamer (Lu et al., 2018), and influence the content of the stream to some extent (Lu et al., 2018). Through our investigation, streamers were found to make use of viewers' pursuit of power (e.g., being the moderator), or engagement within a virtual community. Providing a price for extra services may be interpreted as encouraging and charging for social interactions between streamers and their viewers.

In Behavioral Pattern 2, what motivates viewers to gift is not the content of the stream or the charm of the streamers, but the opportunity to win a prize, which becomes an extrinsic incentive rather than an intrinsic incentive. This appears to be a new property of the online platforms, allowing live streaming to increase revenue through techniques used in other well-established money-making platforms like gambling (Thomas, Allen, & Phillips, 2009).

Both Behavioral Patterns 3 and 4 are about eliciting competitions. They reveal the mutual influences of viewers' interactions. Behavioral Pattern 3 identified a gifting competition between individuals within the same channel, especially involving super-fans or rich viewers. This is consistent with previous research where viewers compete to be the top donor on viewers' fame ranking lists (Sjöblom et al., 2017). To use the direct elicitation technique, streamers need to be aware of changes in the fame ranking lists and the dynamic situation in the stream. In comparison, indirect elicitation is relatively easier since viewers automatically fight for awards from the streamers. That may be the reason why we observed more indirect than direct elicitation.

It appears that some viewers are likely to get involved in and defend their streamers when the situation becomes an intergroup competition (Abrams & Hogg, 1990) in Behavioral Pattern 4. This competition may increase or draw upon viewers' sense of community and group honor, and encourage them to gift more. Our finding is in accord with previous findings that sense of community is an important gifting motivation (Hilvert-Bruce, Neill, Sjöblom, & Hamari, 2018), but here, the sense of community is produced by differentiating the in-group from a relevant out-group, in accord with social identity theory (Tajfel & Turner, 2004).

From our observations, some streamers seem to work collaboratively in live streaming. They seem to purposely create PK/VS competitions with other streamers they know, which stimulates viewers from both sides to gift aggressively in reaction to gifting to the other "rival". In the group competitions, no matter who wins, both streamers involved get benefits. The more intense the competition is, the more gifts the two streamers receive. This imagined or illusive conflict creates an interesting twist on classic theories of social identity-based competition (Abrams & Hogg, 1990; Tajfel & Turner, 2004).

Gender differences in gifting encouragement were noted for the first time in our study. Direct elicitation of competition between male individuals was used exclusively by female streamers. According to previous gender differences study, men respond to status-focused loyalty programs more actively than women, but only when their high status is clear to be noticed by others (Melnyk & van Osselaer, 2012). In the gifting competitions, the gifts a viewer sends to the streamer are always visible to all the viewers in the same channel. Hence, male viewers tend to respond more actively than female viewers in such competition.

## 5.3 | Implications

Our study for the first time systematically explores the behavioral patterns in the special social commerce practice in live streaming, identified four behavioral patterns of gifting encouragement, and reveals some new motivations for digital gifting. In addition, our research contributes to the methods used in behavioral pattern discovery.

Practically, platforms may benefit from our study in terms of marketing and platform design. According to our findings, competition elicitation and prize-winning games have been thought of as useful behaviors by streamers. However, not all platforms have these functions at the moment. Hence, platforms may consider generating similar functions to satisfy viewers' needs. Platforms may organize more contests to create competitive situations. Thus, our findings can be used for reference for marketing-related activities.

Streamers may consider these behaviors and implement them in gifting encouragement. Since the streamers interviewed in our study are popular in the world's largest market, their behaviors can be taken seriously by other streamers. Also, the streamers interviewed come from different popular categories such as game-play, singing, and dancing, hence, the behaviors induced appear to be general and widely used.

## 5.4 | Limitations and future research

Several limitations of this study are acknowledged. In this study, the gifting encouraging behaviors were indicated by streamers, and verified by viewers in the focus groups and investigators' observations. However, the effectiveness of the behaviors has not been formally tested. This calls for experimental designs of quantitative research to test their effectiveness.

Secondly, further analysis is needed on psychological reasons why these behaviors work in gifting encouragement after confirming their effectiveness.

Thirdly, it will be interesting to conduct cross-cultural studies on behaviors of gifting encouragement. This study focused exclusively on the Chinese users and platforms. More studies could be conducted to see if there are any differences in the behaviors for gifting encouragement in other cultures.

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None.

### CONFLICT OF INTEREST

The authors declare no conflict of interest.

### AUTHOR CONTRIBUTIONS

**Xiaoyun Jia:** Conceptualization (lead); data curation (lead); formal analysis (lead); funding acquisition (lead); investigation (lead); methodology (lead); project administration (lead); resources (lead); validation (lead); writing—original draft (lead); writing—review and editing (lead). **Ruili Wang:** Conceptualization (equal); resources (equal); supervision (lead); writing—original draft (equal); writing—review and editing (equal). **James Liu:** Conceptualization (supporting); supervision (equal); writing—original draft (equal); writing—review and editing (equal). **Chuntao Jiang:** Investigation (equal); project administration (supporting); resources (equal); supervision (supporting); writing—review and editing (equal).

### DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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## RELATED WIREs ARTICLES

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## REFERENCES


Abrams, D., & Hogg, M. A. (1990). Social identification, self-categorization and social influence. *European Review of Social Psychology*, *1*(1), 195–228.

Ahmad, M. A. & Srivastava, J. (2014). Behavioral data mining and network analysis in massive online games. In Proceedings of the 7th ACM international conference on web search and data mining (pp. 673-674).

Balan, S., & Rege, J. (2017). Mining for social media: Usage patterns of small businesses. *Business Systems Research: International Journal of the Society for Advancing Innovation and Research in Economy*, *8*(1), 43–50.

Barbier, G., Tang, L., & Liu, H. (2011). Understanding online groups through social media. *WIREs Data Mining and Knowledge Discovery*, *1*(4), 330–338.

Barriball, K. L., & While, A. (1994). Collecting data using a semi-structured interview: A discussion paper. *Journal of Advanced Nursing: Institutional Subscription*, *19*(2), 328–335.

Bohnsack, R. (2004). Group discussion and focus groups. In U. Flick, E. Kardorff, & I. Steinke (Eds.), *A companion to qualitative research* (pp. 214–221). Sage.

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology*, *1*(3), 185–216.

Carter, N., Bryant-Lukosius, D., DiCenso, A., Blythe, J., & Neville, A. J. (2014). The use of triangulation in qualitative research. In *Oncology nursing forum* (pp. 545–547). Oncology Nursing Society.

Chen, Z., Wang, R., Zhang, Z., Wang, H., & Xu, L. (2019). Background–foreground interaction for moving object detection in dynamic scenes. *Information Sciences*, *483*, 65–81.

Clarke, V., & Braun, V. (2017). Thematic analysis. *The Journal of Positive Psychology*, *12*(3), 297–298.

Curty, R. G., & Zhang, P. (2011). Social commerce: Looking back and forward. In *Proceedings of the American Society for Information Science and Technology* (pp. 1-10).

Curty, R. G., & Zhang, P. (2013). Website features that gave rise to social commerce: A historical analysis. *Electronic Commerce Research and Applications*, *12*(4), 260–279.

Decrop, A. (1999). Triangulation in qualitative tourism research. *Tourism Management*, *20*(1), 157–161.

Desai, U., Ramasamy, V., & Kiper, J. (2021). Evaluation of student collaboration on canvas LMS using educational data mining techniques. In *Proceedings of the 2021 ACM southeast conference* (pp. 55-62).

Flick, U. (2004). Triangulation in qualitative research. In U. Flick, E. Kardorff, & I. Steinke (Eds.), *A companion to qualitative research* (pp. 178–183). Sage.

Gros, D., Wanner, B., Hackenholt, A., Zawadzki, P. & Knautz, K. (2017). World of streaming. Motivation and gratification on twitch. In International conference on social computing and social media (pp. 44–57). Springer.

Guest, G., Namey, E., & McKenna, K. (2017). How many focus groups are enough? Building an evidence base for nonprobability sample sizes. *Field Methods*, *29*(1), 3–22.

Guo, J., Yi, P., Wang, R., Ye, Q., & Zhao, C. (2014). Feature selection for least squares projection twin support vector machine. *Neurocomputing*, *144*, 174–183.

Hamilton, W. A., Garretson, O., & Kerne, A. (2014). Streaming on twitch: Fostering participatory communities of play within live mixed media. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 1315-1324).

He, W. (2013). Examining students' online interaction in a live video streaming environment using data mining and text mining. *Computers in Human Behavior*, *29*(1), 90–102.

Hilvert-Bruce, Z., Neill, J. T., Sjöblom, M., & Hamari, J. (2018). Social motivations of live-streaming viewer engagement on twitch. *Computers in Human Behavior*, *84*, 58–67.

iResearch. (2018). 2018 Chinese online game-play live streaming market research report. http://report.iresearch.cn/report_pdf.aspx?id=3254

Jia, X., Wang, R., Liu, J. H., & Xie, T. (2020). How to attract more viewers in live streams? A functional evaluation of streamers' strategies for attraction of viewers. In F. F.-H. Nah & K. Siau (Eds.), *HCI in business, government and organizations* (pp. 369–383). Springer.

Jinriwanghong. (2017). China live streaming industry annual report: How much do streamers earn? Who is gifting? http://www.zhaihehe.com/?/news_detail/762

Lederman, L. C. (1990). Assessing educational effectiveness: The focus group interview as a technique for data collection. *Communication Education*, *39*(2), 117–127.

Lee, Y. C., Yen, C. H., Wang, D., & Fu, W. T. (2019). Understanding how digital gifting influences social interaction on live streams. In *Proceedings of the 21st international conference on human–computer interaction with mobile devices and services* (pp. 1-10).

Liang, T.-P., Ho, Y.-T., Li, Y.-W., & Turban, E. (2011). What drives social commerce: The role of social support and relationship quality. *International Journal of Electronic Commerce*, *16*(2), 69–90.

Lin, X., Li, Y., & Wang, X. (2017). Social commerce research: Definition, research themes and the trends. *International Journal of Information Management*, *37*(3), 190–201.

Lu, Z., Xia, H., Heo, S., & Wigdor, D. (2018). You watch, you give, and you engage: A study of live streaming practices in China. In *Proceedings of the 2018 CHI conference on human factors in computing systems* (pp. 1-13).

Melnyk, V., & van Osselaer, S. M. (2012). Make me special: Gender differences in consumers' responses to loyalty programs. *Marketing Letters*, *23*(3), 545–559.
Ortigosa, A., Carro, R. M., & Quiroga, J. I. (2014). Predicting user personality by mining social interactions in Facebook. *Journal of Computer and System Sciences*, *80*(1), 57–71.
Pahwa, B., Taruna, S., & Kasliwal, N. (2017). Role of data mining in analyzing consumer's online buying behavior. *International Journal of Business and Management Invention*, *6*(11), 45–51.
Restream. (2020). 48 streaming stats you should know in 2020. https://restream.io/blog/live-streaming-statistics/
Ritchie, J., Lewis, J., & Elam, G. (2003). Designing and selecting samples. In L. Maruster & M. J. Gijsenberg (Eds.), *Qualitative research methods* (pp. 79–111). Sage.
Rubin, H. J., & Rubin, I. S. (2012). *Qualitative interviewing: The art of hearing data* (3rd ed.). sage.
Ruggiero, T. E. (2000). Uses and gratifications theory in the 21st century. *Mass Communication & Society*, *3*(1), 3–37.
Sjöblom, M., Törhönen, M., Hamari, J., & Macey, J. (2017). Content structure is king: An empirical study on gratifications, game genres and content type on Twitch. *Computers in Human Behavior*, *73*, 161–171.
Tabassum, S., Pereira, F. S., Fernandes, S., & Gama, J. (2018). Social network analysis: An overview. *WIREs Data Mining and Knowledge Discovery*, *8*(5), e1256.
Tajfel, H., & Turner, J. (2004). An integrative theory of intergroup conflict. In M. J. Hatch & M. Schultz (Eds.), *Organizational identity: A reader* (pp. 56–65). Oxford.
Thomas, A. C., Allen, F. C., & Phillips, J. (2009). Electronic gaming machine gambling: Measuring motivation. *Journal of Gambling Studies*, *25*(3), 343–355.
Thurmond, V. A. (2001). The point of triangulation. *Journal of Nursing Scholarship*, *33*(3), 253–258.
Tu, W., Yan, C., Yan, Y., Ding, X., & Sun, L. (2018). Who is earning? Understanding and modeling the virtual gifts behavior of users in live streaming economy. In *2018 IEEE conference on multimedia information processing and retrieval (MIPR)* (pp. 118-123). IEEE.
Wang, C., & Zhang, P. (2012). The evolution of social commerce: The people, management, technology, and information dimensions. *Communications of the Association for Information Systems*, *31*(1), 5.
Wang, H., Gao, Y., Shi, Y., & Wang, R. (2016). Group-based alternating direction method of multipliers for distributed linear classification. *IEEE Transactions on Cybernetics*, *47*(11), 3568–3582.
Wang, R., Ji, W., Liu, M., Wang, X., Weng, J., Deng, S., Gao, S., & Yuan, C. A. (2018). Review on mining data from multiple data sources. *Pattern Recognition Letters*, *109*, 120–128.
Xinhuanet. (2018). Chinese streamer's occupation report of 2017. http://www.xinhuanet.com/info/2018-01/07/c_136878205.htm
Yu, E., Jung, C., Kim, H., & Jung, J. (2018). Impact of viewer engagement on gift-giving in live video streaming. *Telematics and Informatics*, *35*(5), 1450–1460.
Yu, Y., Gao, Y., Wang, H., & Wang, R. (2018). Joint user knowledge and matrix factorization for recommender systems. *World Wide Web*, *21*(4), 1141–1163.
Zhu, Z., Yang, Z., & Dai, Y. (2017). Understanding the gift-sending interaction on live-streaming video websites. In *9th international conference on social computing and social media* (pp. 274-285).

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