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Internet Celebrity Economy: Exploring the Value of Viewers' Comment Features and Live Streamers' Marketing Strategies in Forecasting Revenue

網紅經濟：檢驗觀眾留言特質和直播主行銷策略對營收之預測價值

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Abstract

Few past studies have tackled the relationship between marketing strategies and revenue forecasts of live streamers, not to mention the influence of streamer heterogeneity. This study applies the Hierarchical Bayesian (HB) model to examine the predictive effects of viewers' comments and streamer' behaviors on viewers' gift-sending behavior in live streaming while considering the effect of streamer heterogeneity. In particular, we empirically analyze 38,183 samples of time data from 10 food live-stream samples. We find that the effects of viewers' comment features and streamers' marketing strategies on viewers' gift-sending behavior are mainly influenced by the cross-level effect of streamers' heterogeneities. These results reveal that existing live-streaming studies might have overlooked the impact of streamers' heterogeneities, offering only biased conclusions. Finally, the model proposed in this study has good predictive accuracy for live streamer revenue.

【Keywords】word-of-mouth, discrete emotion theory, live streamer's behavior and characteristics, gift-sending, Hierarchical Bayesian model

摘 要

過去有關直播主的行銷策略與營收預測之研究十分匱乏，且忽略考慮直播主異質性之影響。本研究應用層級貝氏模型，檢驗在考慮直播主異質性下，觀眾的留言特質和直播主行銷策略對觀眾送禮行為之預測價值。本研究針對 10 部美食直播共 38,183 筆時間資料進行分析，發現留言特質和直播主行銷策略對觀眾送禮行為之效果主要受到直播主異質性的跨層次影響。此顯示過去忽略直播主異質性影響的研究結論可能有偏誤。最後，本研究提出的模型對直播主營收有很好的預測力。

【關鍵字】口碑、分立情緒理論、直播主行為特質、送禮、層級貝氏模型

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1. Introduction

Nowadays, most viewers spend time watching online videos through major live-streaming platforms, such as DouYu, Twitch, and YouTube Live. According to a Fortune Business Insights (2021) survey, the global live-streaming market size is USD 419.03 billion in 2021. Li (2020) reported on March 16, 2020 that China's streamers had created a market of RMB 433.8 billion in 2019. Douyu is the largest live streaming platform in China (Tan, 2019), among which food live streaming is one of the most brilliant live streaming types.[1] Live streaming will continue to grow (Appel, Grewal, Hadi, and Stephen, 2020), and paid gifting becomes a crucial source of revenue for streamers (Zhang, Xiang, and Hao, 2019).

Given the impact of paid gifting on Chinese streamers' revenue, it seems imperative for practitioners of live streamers to understand exactly what influence paid gifting on live-streaming platforms the most. Although existing research has highlighted some of these factors such as viewers' excited comments (Zhou, Zhou, Ding, and Wang, 2019) and emotional attachment (Wan, Lu, Wang, and Zhao, 2017); however, prior studies are still in a relatively nascent stage, and have yet to explore the influence of viewers' various emotion-embedded reactions (e.g., amusement, pride, frustration, or disappointment) on gift-sending behavior thoroughly.

Drawing on emotional arousal theory, we argue that distinct emotions have differing effects on gift-sending behavior. Emotions are highly diverse and complex and cannot be reduced to a simple positive-negative distinction (Lerner and Keltner, 2000; Yin, Bond, and Zhang, 2014). Therefore, exploring the effects of various emotion-embedded comments on viewers' gift-sending behavior during live streaming becomes essential when conducting research regarding streamers' revenue forecasts (Lin, Yao, and Chen, 2021).

Furthermore, although the importance of comment metrics has been recognized,[2]

1 Information Café (2022)

2 Prior studies have often adopted the terms of comment, review, and word of mouth (WOM) to represent message metrics in academic parlance. Mudambi and Schuff (2010) define online comments (or reviews) as peer-generated product evaluations posted on company or third party websites. Hennig-Thurau, Gwinner, Walsh, and Gremler (2004) define online WOM as any positive or negative statements made by potential, actual, or former customers about a product or company, which is made

scholars have not reached consistent conclusions yet. Liu (2006) finds that it is the volume, not the valence[3] of online comments has explanatory power for sales. Conversely, Chintagunta, Gopinath, and Venkataraman (2010) find not the volume, but the valence of comments has explanatory power. And interestingly, Dellarocas, Zhang, and Awad (2007) find that both the volume and valence of comments have explanatory power. Although these studies have established comments as significant factors and predictors of product sales, none of them have offered concrete models that managers can adopt in their decision-making.

It is evident that comments represent a potentially valuable tool for streamers to monitor viewers' attitudes in real time and adapt marketing strategies accordingly. Thus, it is critical to develop predictive models and metrics in harnessing these comments (Chung, 2011). As predictive models are usually forward looking, inevitably, the omission in theoretical development causes most academic work becomes irrelevant to real-world situations (Shmueli, 2010). To bridge the gap between methodological development and practical application (Singleton, Mclean, and Altman, 1988), and to meet the future trend of using predictive models to satisfy practical needs (Shmueli and Koppius, 2011), developing a predictive model through theoretical development becomes necessary (Shmueli, 2010).

However, prior studies have not adequately acknowledged that one model cannot fit the entire population of streamers who could have major segments in terms of personal characteristics. For example, Wohn and Freeman (2020) find that streamers' attractiveness and worth have explanatory power over viewers' intention to donate during live streaming. Wan et al. (2017) find that streamers' personalization and sociability affect the donation intention of viewers. Unfortunately, most prior livestream studies have ignored the fact of streamer heterogeneity (Bharadwaj, Ballings, Naik, Moore, and Arat, 2022). These studies have treated all data alike, neglecting difference in individual-level characteristics (i.e.,

available to a multitude of people and institutions via the Internet. These terms are highly relevant (Huang and Liu, 2016). Although this research focuses on comments, some studies on WOM and reviews are also referred to and cited in this study.

3 Volume indicates the total number of WOM messages, while valence indicates the preference of comments (expressed as positive/negative/neutral) (You, Vadakkepatt, and Joshi, 2015).

streamer heterogeneity, which creates challenges to data analysis. And when these analyses are hard to execute rigorously, other researchers are not able to replicate it (Allenby, Rossi, and McCulloch, 2005). Thus, considering the individual heterogeneity in the predictive model is necessary (Lee, Cho, Lee, and Lee, 2006; Van den Bulte and Joshi, 2007). To fill this research gap, this study applies the Hierarchical Bayesian (HB) model to handle sample heterogeneity.

This study provides an overarching framework that addresses the existing deficiencies aforementioned by exploring the predictive value of viewers' emotion-embedded comments, comment metrics, and streamer heterogeneity and behavior on streamers' revenue from live streaming. In other words, we propose a revenue forecasting model tailored to the livestream industry, and test streamers' performances in the context of live-streaming revenue forecasting. Surprisingly, we find that prior livestream studies that examined the factors influencing streamers' revenue may have offered biased conclusions because they ignore the impacts of streamer heterogeneity.

2. Literature Review and Inference Developement

This section introduces live-streaming platforms and proposes three theories to explain the variables that predict viewers' gift-sending behavior on a live-streaming platform presented in prior literature.

2.1 Live-Streaming Platforms

In recent years, live-streaming platforms have emerged as a unique form of social media (Hu, Zhang, and Wang, 2017). With the help of cutting-edge internet technologies, live-streaming platforms offer text and image features and audio and video functions. Unlike traditional social media, such as virtual communities and blogs, a live streaming platform allows its users (e.g., internet celebrities; also known as wanghong in Chinese) to stream performances, games, or daily life activities on a real-time basis. These streamers can also engage in dialogue or interact with their viewers while streaming. Viewers, in turn, can not only chat with each other through text-based messages but also leave real-time comments for the streamers, which appear in the form of a ticker across the screen, and send virtual gifts to the streamers (see Appendix for the gift examples). The virtual gifts are bought from the live-streaming platform using real-world money. This latest internet technology (i.e. virtual paid gifting) has contributed a new business model to the gift economy (Zhang et al., 2019). Figure 1 is an image of a typical live-streaming channel captured from DouYu (douyu.com), one of China's most famous live-streaming platforms (Zhou et al., 2019). In the live-streaming platform, viewers can send comments or virtual gifts in danmaku.[4]

While viewers in China are fairly familiar with the paid gifting function, and paid gifting also contributes a large amount of revenue to firms running the live-streaming platforms (Zhou et al., 2019); however, paid gifting is relatively new in the western markets, and some US-based live streaming platforms such as Twitch and YouTube Live, have just begun generating revenue from this concept in recent years (Bearne, 2017).

Figure 1 Channel Page on DouYu

In addition to the novel feature of paid gifting, live streaming platforms are quite distinct from each other in terms of their streaming contents, primary sources of revenue, or interactive functions. Twitch, for example, livestreams various games and offers interactive functions similar to those of DouYu (e.g., the streamer interacts with the

4 Danmaku is shown in the comments in Figure 1, which means that viewers can post their comments while watching a live stream. The subtitles will be displayed in real-time when all viewers watch the live stream, thus increasing the interaction between the viewers.

viewers during the gameplay process). However, its primary revenue source is the viewer subscriptions to the streamers (Sjöblom and Hamari, 2017), not from the paid gifting. YouTube Live livestreams a wide range of issues (e.g., news, sports, and education), and its revenue also mainly came from viewer subscriptions; but YouTube Live does not offer interactive functions as rich as those of DouYu.

2.2 Impact of Viewer Comment Metrics on Paid Gifting

Existing research on experience products has discussed how the metrics of online comments (or word of mouth) impact product revenue (Huang, C. and Liu, P., 2016; Ni, Li, and Lin, 2021). The results of early studies on the explanatory powers of comment metrics are consistent with theoretical predictions and with each other. Table 1 compares the effects of two key comment metrics on product revenue. While most scholars have stated that the volume of comments positively influences revenue (e.g., Liu, 2006; Dellarocas et al., 2007; Duan, Gu, and Whinston, 2008; Zhou et al., 2019), some has indicated that it has no effect (e.g., Chintagunta et al., 2010). Chintagunta et al. (2010) further explain that volume positively influences the box office only under the condition of higher comment valence. Similarly, Table 1 shows that a majority of the scholars have suggested that comment valence positively influences revenue (e.g., Dellarocas et al., 2007; Duan et al., 2008; Chintagunta et al., 2010).

On live-streaming platforms, sending gifts to streamers signifies viewers' affinity toward the streamers, while comments indicate viewers' desire to interact with or express opinions about the streamers, or with other viewers. Given that live-streaming platforms have the advantage of instant communication, this study assumes that streamers' behaviors and viewers' comments would affect particular viewers' gift-sending behavior. However, the coding of viewers' comments is a tedious task and considerably constrains data using and examination. Zhou et al. (2019) work is the only research so far to show indirect evidence that the number of words used in a viewer's comments has explanatory power over gift giving during live streaming. Their findings imply that the higher the volume of viewer comments, which are positive in nature, the more frequent gift-sending behavior happens. Given the discussion thus far, this study infers that the volume and valence of comments are positively related to viewers' gift-sending behavior on live-streaming platforms.

Table 1 The Effects of Comment Metrics on Revenues

Studies	Product Domain	Method	Key Comment Metrics	Effects of Comment Metrics
Godes and Mayzlin (2004)	TV show	Web Crawling/ Regression	Volume and valence	Valence increases TV ratings
Dellarocas et al. (2007)	Movies	Web Crawling/ Bass model	Volume and valence	Both volume and valence increase box office revenue
Duan et al. (2008)	Movies	Web Crawling/ 3SLS Regression	Volume and valence	Both volume and valence increase box office revenue
Chintagunta et al. (2010)	Movies	Web Crawling / Regression	Volume and valence	Valence increases TV ratings
Moon, Bergey, and Iacobucci (2010)	Movies	Web Crawling/ Regression	Volume and valence	Volume decreases satisfaction
Wang and Yu (2017)	Social media	Questionnaire design/ Regression	Volume and valence	Both volume and valence increase box office revenue
This study	A live-streaming website	Web Crawling/ Hierarchical Bayesian Model	Volume and valence	Both volume and valence increase gift-sending behavior under the specific conditions of the streamer's characteristics

2.3 Impact of Viewers' Discrete Emotional Comments on Viewers' Paid Gifting

Emotions are “a mental state of readiness that arises from cognitive appraisals of events or thoughts” (Bagozzi, Gopinath, and Nyer, 1999). Discrete emotion theory suggests that emotions include numerous positive (e.g., joy, surprise, amusement, entertainment, enjoyment, interest, and happiness) and negative emotions (e.g., sadness, anger, anxiety, surprise, fear, frustration, and disappointment) delineated as semantic epithets (Teixeira, Wedel, and Pieters, 2012). Emotions play a vital role in comments since the emotion expressed in a user's comment affects directly toward specific purchase experiences (Yin et al., 2014). Table 2 lists recent studies regarding the effects of viewers' emotions on paid gifting during live streaming. Phonthanukitithaworn and Sellitto (2017), for example, state that viewers feel excitement and joy when using Facebook to watch live sports telecasts, and these emotions indirectly affect their behavioral intentions. Similarly, the higher the viewers' interest in a streamer, the more likely they are to donate to that content creator (Wan et al., 2017). However, these studies have not adequately addressed the impact of distinct emotions on paid gifting and which discrete emotions embedded in comments have a greater influence on gift-sending behavior.

Table 2 The Effects of Viewers' Emotions on Paid Gifting in Live-Streaming

Studies	Media	Theory	Method	Dependent Variable	Discrete Emotions
Phonthanukititha-worn and Sellitto (2017)	Facebook (Live Telecasts of the EPL)	Purposive needs, emotion, social camaraderie, Subjective Norm	Questionnaire design/ Structural equation modeling	Behavioral Intention	● Excitement ● Joyful
Wan et al. (2017)	YY platform (a live-streaming video website)	Social-technical systems and attachment theory	Questionnaire design/ Structural equation modeling	Intent to donate to content creator	● Interesting
Zhou et al. (2019)	Douyu.com (a live-streaming website)	Social interaction theory	Web Crawling/ Regression	Gift-sending behavior	● Excitement
This study	Douyu.com (a live-streaming website)	Discrete emotion	Web Crawling/ Hierarchical Bayesian Model	Gift-sending behavior	Positive emotion: ● Excitement ● Amused ● Praising Negative emotion: ● Complaining ● Disappointed ● Ridiculing

Several prior studies have indicated that online product reviews influence sales and performance. For instance, Chen and Teng (2013) highlight the importance of online store owners' ability to provide entertaining interfaces for their online shoppers. Tang and Zhu (2019) show that when consumers perceive that a product has high risk, praise-embedded comments by other users on an O2O (online to offline) website, which would positively impact their intentions to purchase the product. On the other hand, mismanaged complaints decrease a firm's sales (Turney and Littman, 2003). Consumers, particularly women, experience a decline in purchase intentions after reading a disappointed review (Bae and Lee, 2011). And so far no study has supported the effect of "ridiculing" comments on purchasing behavior. Nevertheless, Ullah, Amblee, Kim, and Lee (2016) suggest that negative emotions can improve producer offerings; that is, the use of words such as "ridiculing" to describe a product can trigger a continuous process of quality improvement, which can significantly benefit the producer firm.

Compared to above-noted studies regarding online product reviews in e-commerce environments, research on the relationship between discrete emotional features in viewers' comments and their gift-sending behavior has been insufficient in the context of livestream environments. Drawing on the aforementioned literature, this study infers that comments embedded with positive emotions (i.e., excitement, amusement, and praise) are positively related to viewers' gift-sending behavior on live-streaming platforms. Conversely, negative emotional comments (i.e., criticism, disappointment, and ridicule) detrimentally impact viewers' gift-sending behavior on live-streaming platforms.

2.4 Impact of Streamers' Characteristics and Behaviors on Paid Gifting

Table 3 lists the effects of streamers' characteristics and behaviors on viewers' gift-sending and donation intentions on live-streaming platforms. Most studies included in the table have examined the impact of streamers' behaviors on viewers' gift-sending intentions rather than behavior, on live-streaming platforms from a socio-psychological perspective. For example, Wan et al. (2017) examine the effect of social and technological factors on the donation intention of livestream users and find that both interaction and information value have an indirect influence. Yu, Jung, Kim, and Jung (2018) adopt a social perspective to explain that chatting with other viewers enhances viewers' gift-sending behavior. Wohn and Freeman (2020) show that value creation by streamers through, for example, the sharing of product features and experiences increases viewers' willingness to pay for gifts. Xu (2017) suggests that enthusiastic responses by streamers play a critical role in product marketing.

Few studies, however, have explored the impact of streamers' characteristics on gift-sending intentions. Wohn and Freeman (2020), for example, suggest that the interpersonal attractiveness of streamers positively impacts donation intentions and that female streamers may have a stronger impact on viewers' perceptions. Wan et al. (2017) state that streamers' personal characteristics, such as personality and sociability, indirectly influence donation intentions. From a hosting style perspective, Vraga, Edgerly, Bode, Carr, Bard, Johnson, Kim, and Shah (2012) indicate that sociability increases perceptions of information value and enhances host credibility and that humor influences audience likeability toward the host. Chang, Zhu, Wang, and Li (2018) further suggest that an advocate's persuasiveness positively influences participants' attitude changes. These findings imply that hosting styles, such as sociable, comical, and persuasive, play an important role in influencing viewers' behaviors. In addition, although there has been no research to examine the effects of food streamers' behavior on their revenue, we often see successful food streamers share food features, cooking skills, or tasting experiences during live streaming. Based on the above discussions, this study infers that streamers' behaviors (i.e., chatting with the viewers, responding to viewers' questions, sharing food features, sharing cooking skills, and sharing tasting experiences) and characteristics (i.e., gender, physical attractiveness, and hosting styles) may influence their revenues.

3. Data and Methods

This study examines the effects of viewers' comments features and streamers' behvaior on viewers' gift-sending behavior during live streaming. To do so, we employ the following three steps. (1) Data collection and preprocessing: in this step, we use DouYu as our data source to collect the content of viewers' comments and viewers' gift-sending numbers in food live streaming. We then use word segmentation methods and word frequency statistics for data preprocessing. (2) Sentiment analysis: in this step, we use sentiment analysis to analyze the viewers' comment content. (3) Streamers' behavior coding: we code streamers' behavior during live streaming.

3.1 Data Collection and Preprocessing

The dataset used to evaluate the gift sending behavior of the proposed models contained 10 food streamers on the live-streaming platform released from March 1 to April 15, 2019, with comments and gifts sent from viewers, as well as streamers' characteristics and behaviors. The data consist of 38,183 seconds of live-streaming data,

Table 3 The Effects of the Characteristics and Behaviors of Streamer on Paid Gifting in Live-Streaming

Studies	Product Domain	Theory	Methodology	Dependent Variable	Streamers' Behaviors	Streamers' Characteristics
Wan et al. (2017)	YY live-streaming	Social-technical systems and attachment theory	Questionnaire design/ Structural equation modeling	Emotional attachment/ Functional dependence/ Donate Intent	● Interaction with viewers ● Providing information value	● Personalization ● Sociability
Yu et al. (2018)	TV Live-streaming	Theory of social interaction	Dataset	Gift-sending behavior	● Chatting with the viewers	×
Wohn and Freeman (2020)	eSport game in Live-streaming	Theory of emotional attachment and attractiven-ess	Questionnaire design	Gift-sending intention	● Streamer's worth	● Attractive-ness
Zhang et al. (2019)	Live video streaming	Reciprocity	In-depth interview	Gift-sending intention	● Communicating with the viewers ● Reciprocal relationship	×
This study	Douyu. com (food streamer in live-streaming)	Theory of Social psychology and host style	Web Crawling/ Hierarchical Bayesian Model	Gift-sending behavior	● Chatting with the viewers ● Responses to viewers' questions ● Sharing food features ● Cooking skill sharing ● Tasting experience sharing	● Gender ● Outward beauty Host style: ● Sociability ● Comic ● Persuasive

28,575 comments, and 44,787.3 RMB of gift values. The average gift value across all live streaming is equal to 4,478.7 RMB, and the average comment volume is 2,857.5 per live stream.

The data includes the time-varying behaviors of viewers per second in each food live stream, such as sending comments or gifts in danmaku (Zhou et al., 2019). We collect all recordings of danmaku in the DouYu live-streaming website using the obs web crawler program (http://www.obsapp.com/apps/obsdanmu/), which can crawl through both historical comment contents and the numbers of gifts sent during each live stream. We calculate the number of comments in each live stream from the release period, including the first comment and gift posted to the last ones posted after the live stream finished.

We chose Douyu over other possible platforms because of the following reasons: (1) paid gifting is originally invented by Chinese companies (Zhou et al., 2019) and has been widely adopted by Chinese live-streaming firms. (2) DouYu is the most top live-streaming platforms in China as mentioned previously (Tan, 2019). DouYu had approximately 46.71 million active users in January 2019.[5] The platform focuses on streaming such content as food, mobile games, travel, music, cars, science, sports, and other recreational activities. (3) DouYu requires no access fee for either browsing the live streams or posting a comment; therefore, it can attract more viewers, and the research data will be more diverse. (4) The DouYu website is well designed so that information collection is straightforward, thus reducing error during data collection. Thus, it is possible to track the timepoint in the live stream's run to which a particular comment belonged.

As mentioned previously, Zhou et al. (2019) measure the numbers of donations received by streamers and the comment features of viewers at the minute level during a live-streaming period. However, since viewer donations are partly dependent on what streamers air, it is logical to consider the streamers' behaviors when examining the reasons for donations. In terms of collecting data on streamers' behaviors, this study downloads each live-streaming video and performs content analysis for each streamer behavior. In addition, Zhou et al. (2019) only use the fixed time span of "one minute" as the analysis unit, which cannot effectively identify the distribution patterns hidden in streamer behaviors and gift-sending information. One reason is that it is not reasonable to divide the streamers' behaviors into units per minute. Further, the viewers' behaviors are mainly affected by streamers' behaviors, and viewers' comments or donations are the results of their lengthy considerations; a viewer's behavioral state will have a carryover effect. Therefore, to capture fully the relationship between the behaviors of the streamer and those of the viewers, this study uses seconds as the time span unit and observes the correlation between the streamer behaviors and viewer behaviors as a basis for correction. Specifically, this study codes 1 at five seconds before the viewer behavior occurs (such as sending a comment or donation), ten seconds after the viewer behavior occurs as well as ten seconds after the

5 Miss Game (2019)

streamer behavior occurs. Moreover, DouYu offers several types of gifts as donations, and the value of each gift is different. However, Zhou et al. (2019) only calculate the number of gifts, which might have produced significant measurement errors. This study revises the coding of the gift values according to the gift values provided by the DouYu website (See the appendix).

This study extracts the following attributes for each live-stream show on food products: (1) reviewer ID, (2) time at which viewers post a comment, (3) time at which the streamer receives a gift, (4) content of the comments, and (5) the characteristics and behaviors of the streamers. Information extracted from viewers' comments can be classified in terms of volume and valence. Besides, discrete emotion is extracted from the content of viewers' comments.

3.2 Sentiment Analysis

Given the wide variations in the features of various social media platforms, this study performs a sentiment analysis of the emotional features of comments on live-streaming platforms. We divide the viewers' comments into eight categories as follows: volume, positive, negative, excited, amused, ridiculing, complaining, and disappointed. Because the danmaku appeared in the 10 streaming channels are written in Chinese, this study adopts the package jiebaR[6] to perform word segmentation. To identify the valence (i.e., positive, negative, and neutral) and emotion (i.e., excited, amused, praising, complaining, disappointed, and ridiculing) of a word, we adopt the text segmentation technique. First, we use an emotion dictionary code called the "National Taiwan University Semantic Dictionary in tmcn[7] (Li, 2019)" to infer the valence and emotion of a word. Second, we mark the words with the valence or the emotion. This study calculates the volumes of the total comments, positive comments, negative comments, and comments with various discrete emotions every second. At the end of this procedure, a final coding is assigned to

6 Package "jiebaR" is a vetted package that provides Chinese text segmentation, keyword extraction, and speech tagging. Proir studies have adopted this package (e.g., Zhou et al., 2019).

7 Package "tmcn" is also a vetted package that provides the text mining toolkit for simplified Chinese, which includes facilities for Chinese string processing, Chinese NLP supporting, encoding detecting and converting. Moreover, it provides some functions to support the 'tm' package in Chinese. This package has been widely used in practice.

each category, representing the words in the text sample matching that category. Notably, the classification system includes categories for a variety of emotional dimensions, making it sensitive to the differences among discrete emotions.

4. Forecasting Model of Internet Streamer Revenues

Prior studies on viewers' gift-sending behavior in live streaming have ignored the effects of streamer heterogeneity (e.g., physical attractiveness or personalization). These studies lack data at the individual-level and treat all data alike, which create severe challenges to the analysis of marketing data, making it hard to execute in a rigorous manner that lends itself to replication by other researchers (Allenby et al., 2005). The HB model helps solve the problem of insufficient sample information and provide better forecasting accuracy (Lin, Chen, and Jen, 2007; Lynch, 2007). This study adopts the HB model to study the effects of viewers' comments and streamers' behaviors on viewers' gift-sending behavior in live streaming under the premise of considering streamer heterogeneity. Specifically, we measure the revenue of streamers (y), donations from viewers are included, on live-streaming platforms within the context of a normal distribution. We also calculate streamer value $E(y)$, which emphasizes potential revenue streams as well. A standard HB model equation is as follows.

It is assumed that y_{ij} is the value of the j^{th} gift sent to the i^{th} streamer. Then, we have

$$y_{ij} \sim Normal\left(\beta_i x_{ij}, \sigma^2\right), \tag{1}$$

where x_{ij} are dummy variables denoting the vectors of the comment metrics (i.e., total number, positive comments, and negative comments), discrete emotional comments (i.e., excited, amused, praising, complaining, disappointed, and ridiculing), andstreamers' behaviors (i.e., chatting with viewers, sharing food features, responding to questions from viewers, showing the cooking process, and sharing tasting experiences) in the i^{th} live streaming. β_i is a $k \times 1$ ($k = 14$) matrix representing viewers' gift-sending behavior structure and is normally distributed.

$$\beta_i \sim MVN(\Gamma d_i, \Omega), \tag{2}$$

Table 4 Hierarchical Bayesian Estimates (Posterior Standard Deviation)

Parameter		1	2	3	4	5	6	7	8	9	10
Comment Metrics	*Total Comment Volumes*	.751	.487	-.062	.219	.165	.135	.574	.247	.562	.203
		(.296)	(.421)	(.354)	(.571)	(.596)	(.306)	(.257)	(.306)	(.888)	(.320)
	Positive Comment	1.007	.348	.250	.304	5.400	-.182	2.092	.107	.401	1.151
		(.415)	(.500)	(.595)	(.719)	(.851)	(.501)	(1.046)	(.416)	(1.104)	(.503)
	Negative Comment	.765	.426	.164	.188	4.575	.081	3.178	.378	.444	.204
		(.572)	(.550)	(.729)	(.660)	(.997)	(1.221)	(1.251)	(.572)	(1.075)	(1.162)
Discrete Emotion Comments	*Exiting Comment*	.658	-.133	-.213	.315	2.426	-.610	-.197	-.260	-.775	-.187
		(.306)	(.523)	(.772)	(.608)	(1.185)	(.711)	(1.113)	(.703)	(.930)	(.937)
	Amused Comment	-.553	-.810	-1.664	-.603	-3.548	-.123	-3.590	-1.193	-.387	-1.669
		(.730)	(.810)	(1.099)	(.648)	(.924)	(1.045)	(2.308)	(.955)	(1.647)	(1.068)
	Praising Comment	-.007	-.157	-.025	-.014	-.007	2.177	1.104	-.128	.068	-.891
		(.568)	(.611)	(.670)	(.599)	(1.394)	(.496)	(1.491)	(.815)	(1.037)	(.525)
	Complaining Comment	.229	.528	.548	.433	1.144	3.066	2.765	.440	1.104	-.752
		(.587)	(.587)	(.708)	(.596)	(.890)	(.834)	(1.116)	(.690)	(1.091)	(.968)
	Disappointed Comment	.183	-.240	-.148	.228	-.769	.767	.113	-.295	.061	-.527
		(.659)	(.663)	(.769)	(.597)	(.769)	(2.050)	(1.837)	(.934)	(1.173)	(1.152)
	Ridiculing Comment	.268	-.541	-.759	-.006	-2.272	-.574	-1.275	-.735	-.276	-.800
		(.605)	(.607)	(.814)	(.698)	(1.333)	(.939)	(1.667)	(.897)	(1.127)	(.948)
Streamers' Behavior	*Chatting with the Viewers*	-.185	1.347	1.322	.083	-3.215	6.668	1.795	1.565	1.785	-1.514
		(1.160)	(.606)	(1.174)	(.849)	(1.318)	(1.259)	(.908)	(.915)	(.995)	(.978)
	Responding to the Viewers' Question	.950	.638	.324	1.074	-2.605	.641	-.714	.201	.847	1.610
		(.731)	(.753)	(.582)	(.517)	(.695)	(.477)	(1.088)	(.545)	(1.112)	(.485)
	Sharing Food Features	.995	-.365	.380	-.863	5.699	-1.271	2.874	.450	-.653	.951
		(1.035)	(.665)	(1.152)	(.826)	(.976)	(.935)	(1.218)	(.651)	(1.282)	(.667)
	Showing the Cooking Process	-1.017	.445	-.061	-.454	-2.321	4.951	2.583	.153	1.391	-1.941
		(.904)	(.576)	(.996)	(.836)	(.599)	(1.602)	(1.332)	(.943)	(1.677)	(1.910)
	Tasting Experience Sharing	.680	.228	-.022	.855	-4.103	.683	-2.272	-.146	.025	.085
		(1.396)	(1.278)	(.886)	(.377)	(.693)	(1.764)	(1.890)	(1.355)	(1.711)	(1.891)

where d_i is a $P \times 1$ ($P = 5$) matrix, which are dummy variables that denote the presence of streamer heterogeneity (i.e., gender, physical attractiveness, and hosting style). Γ is represented by a $k \times P$ matrix that measures the relationship between viewers' gift-sending behavior structure and streamer heterogenity. Ω is the positive definite covariance matrix of $k \times k$.

The model allows for heterogeneity in the mean vector and covariance matrix of the normal distribution and thus reflects heterogeneous behaviors in terms of levels (β_i) and variability (σ^2). The HB model with normal distribution assumes that the mean vector β_i is normally distributed across viewers and employed an inverted gamma distribution for σ^2, that is, $\sigma^{-2} \sim Gamma(a_0, a_1)$.

The core of the HB model accounts for the uncertainty of the sample (Chiang, Chib, and Narasimhan, 1999). Accounting for uncertainty is critical whenever data limitations exist that lead to imprecise inferences about any aspects of behavior (Allenby et al., 2005). HB models are a combination of two things: (1) a model written in a hierarchical form that is (2) estimated using Bayesian methods (Allenby et al., 2005). We can analyze the marketing data using one model for within-unit analysis and another model for across-unit analysis (Allenby et al., 2005). The within-unit model could be used to describe the viewers' behaviors (e.g., viewers' commenting or gift sending) over time, while the across-unit analysis could be used to describe the heterogeneity (e.g., the streamer's outward beauty) of the units (Jen and Chen, 2007; Rossi, Gilula, and Allenby, 2001). The sub-models are combined to form the hierarchical model, and Bayes theorem is used to integrate the pieces and account for all the uncertainty that is present (Allenby et al., 2005). Furthermore, with the development of computational methods, Markov Chain Monte Carlo (MCMC) method replaces the past complex analysis required to implement Bayes' theorem (Haugh, 2017).

5. Estimation and Results

This section reports the estimation results for 10 live-streaming data and investigates the performance of the proposed HB model. Specifically, we use the HB model to examine the effects of comment features and the behaviors of streamers on the gift-sending behavior of viewers (see Table 4) and the cross-level effects of streamer heterogeneity (see

Table 5). The three determinants included (1) three comment metrics (i.e., volume, positive comments, and negative comments), (2) discrete emotions (i.e., excited, amused, praising, ridiculing, complaining, and disappointed), and (3) streamers' characteristics (i.e., gender, facial attractiveness, sociable style, persuasive style, and comical style) and behaviors (i.e., chatting with viewers, sharing food features, responding to viewers' questions, sharing cooking, and tasting food processes). The comment metrics and discrete emotional features of the viewers' comments are qualitative variables and treated with dummy variables. This study adopts the package rjags[8] for Bayesian data analysis. The parameter estimation of the HB model uses Gibbs sampling with over 10,000 MCMC iterations, of which the first 10,000 iterations are discarded and the last 10,000 iterations are used to form estimates of the posterior distribution of the HB model parameters.

The HB model is shown to offer a less restrictive method of pooling to obtain an aggregate measure of the influence of the explanatory variables (Allenby, Jen, and Leone, 1996). One of the reasons is because the HB model assumes that the coefficients for each live stream come from a common distribution. The beta is normally distributed, and the parameters a_0 and a_1 of the prior distribution of the σ^{-2} are given as $a_0 = a_1 = 0.01$. Ω^{-1} is distributed in the Wishart distribution: $W_k\ (\gamma,R)$, and it is assumed that the diagonal elements of R are all equal to 1, the rest are equal to 0, and parameter γ is set to equal to 1. Heterogeneity in response to the explanatory variables is observed when pooling data across live streaming. Equation 2 serves to shrink the posterior coefficient estimates for each live stream toward a hyperparameter. In addition, we have to assess the convergence of MCMC simulations toward the posterior distribution. This study uses the Heidelbergr and Welch (H-W) diagnostic to detect the model. This method calculates a test statistic (based on the Cramér-von Mises test statistic) to accept or reject the null hypothesis that a Markov chain is from a stationary distribution. The results show that the chain passed the H-W diagnostic.

8 Package "rjags" is a vetted package that provides an interface from R to the JAGS library for Bayesian data analysis and has been cited by many studies (e.g., Coblentz, Rosenblatt, and Novak, 2017; Ramírez-Hassan and Montoya-Blandón, 2020). JAGS uses Markov Chain Monte Carlo (MCMC) to generate a sequence of dependent samples from the posterior distribution of the parameters.

The coefficient estimates (i.e., the mean of the posterior distribution for each coefficient) for the HB model are shown in Table 4. When the posterior estimates are compared to the posterior standard deviations, some coefficients of the metrics (e.g., total or positive comments; see bold numbers in Table 4), discrete emotions (e.g., complaining comments), and streamers' behaviors (e.g., chatting with viewers or sharing food features) are "significant" at $\alpha = .05$ using a one-sided test (Allenby et al., 1996). Although only a few coefficients of the specific variable (i.e., positive comments) appear to have a significant, consistent effect on the viewers' gifting behavior across 10 live-streaming data, this result shows that the heterogeneity of the streamers had a cross-level effect on these relationships.

Table 5 shows that estimates of the hyperparameters (i.e., gender, physical attractiveness, and streamers' hosting styles) provides a useful summary of the comment metrics, discrete emotions, and streamers' behaviors. In other words, streamer heterogeneity has cross-level effect on the relationships between the viewers' comment metrics and discrete emotions and between streamers' behaviors and viewers' gift-sending behavior. Past research (e.g., Wohn and Freeman, 2020; Yu et al., 2018; Zhou et al., 2019) has only discussed the use of the OLS method, which may have led to biased results because they all ignore the significant impact of streamer heterogeneity. Specifically, in terms of gender effect, this study finds that compared to female streamers, the more male streamers chat with the viewers (*M* = 1.245, *SD* = .620),[9] the higher the viewers' gift-sending behavior.

Second, the streamer with higher outward beauty has more excited comments (*M* = 1.221, *SD* = .606), and the more she/he chats with the viewers (*M* = 1.203, *SD* = .601) and responds to questions (*M* = 1.178, *SD* = .587), the higher the viewers' gift-sending behavior.

Third, in terms of streamers' hosting styles, a sociable streamer has more total (*M* = 1.232, *SD* = .608), negative (*M* = 1.468, *SD* = .598), and complaining (*M* = 1.409, *SD* = .597) comments, and the more he/she responds to questions (*M* = 1.211, *SD* = .603) and shows the cooking process (*M* = 1.522, *SD* = .617), the higher the viewers' gift-

9 *M* is an abbreviation for the posterior mean, and *SD* is an abbreviation for the posterior standard deviation. These abbreviations are also used hereafter.

Table 5 Hierarchical Bayesian Estimates of Hyperparameters (Posterior Standard Deviation)

Parameter		Gender (Male)	Physical Attractiveness (Outward Beauty)	Streamers' Host Style		
				Sociability	Persuasive	Comic
Comment Metrics	*Total Comment Volumes*	1.001	1.001	1.232	.914	.661
		(.598)	(.607)	(.608)	(.607)	(.516)
	Positive Comment	1.095	.959	1.167	.972	.867
		(.623)	(.604)	(.597)	(.623)	(.551)
	Negative Comment	1.008	.841	1.468	1.200	.836
		(.599)	(.604)	(.598)	(.606)	(.558)
Discrete Emotion Comments	*Exiting Comment*	.981	1.221	.803	1.062	1.282
		(.609)	(.606)	(.598)	(.611)	(.568)
	Amused Comment	.828	1.100	1.076	.894	1.065
		(.619)	(.609)	(.616)	(.616)	(.576)
	Praising Comment	.920	1.012	1.078	1.246	1.345
		(.606)	(.601)	(.609)	(.608)	(.567)
	Complaining Comment	1.147	.863	1.409	1.001	1.258
		(.619)	(.616)	(.597)	(.614)	(.549)
	Disappointed Comment	.955	.998	1.159	.979	1.269
		(.593)	(.608)	(.616)	(.602)	(.567)
	Ridiculing Comment	.930	1.053	1.154	.999	1.188
		(.616)	(.589)	(.614)	(.603)	(.570)
Streamers' Behavior	*Chatting with the Viewers*	1.245	1.203	1.189	1.213	1.282
		(.620)	(.601)	(.638)	(.629)	(.615)
	Responding to the Viewers' Question	.986	1.178	1.211	.869	.824
		(.619)	(.587)	(.603)	(.618)	(.559)
	Sharing Food Features	1.207	.946	1.208	1.298	1.076
		(.618)	(.635)	(.634)	(.636)	(.615)
	Showing the Cooking Process	.990	.848	1.522	.962	1.101
		(.613)	(.614)	(.617)	(.618)	(.584)
	Tasting Experience Sharing	1.021	1.209	.977	1.003	1.220
		(.652)	(.623)	(.618)	(.618)	(.624)

sending behavior. Further, a persuasive streamer has more praising (M = 1.246, SD = .608) comments, and the more he/she shares food features (M = 1.298, SD = .636), the higher the viewers' gift- sending behavior. In addition, a comical streamer has more excited (M = 1.282, SD = .568), praising (M = 1.345, SD = .567), complaining (M = 1.258, SD = .549), disappointed (M = 1.269, SD = .567), and ridiculing (M = 1.188, SD = .570) comments, and the more she/he chats with the viewers (M = 1.282, SD = .615), the higher the viewers' gift-sending behavior.

6. Forecasting Accuracy

We perform Leave-one-out Cross-validation (LOOCV) to evaluate the HB prediction model. James, Witten, Hastie, and Tibshirani (2013) indicate that LOOCV is K-fold cross-validation taken to its logical extreme, with K equal to N, the number of data points in the set. This means that for N separate times, the function approximator is trained on all data except for one point, and a prediction is made for that point. We add three new live streams with a total of 13 data points for analysis. Therefore, this study conducts the analysis 13 separate times, where we use 12 streams for training versus one live stream for holdout, repeating such that each stream gets a chance to be out-of-sample once. Two quality indices are computed for model validation: Mean Absolute Error (*MAE*) and the Root Mean Squared Error (*RMSE*). The *MAE* is equal to the absolute difference between the actual value of gift giving and posting observed at time step t, throughout the duration of the lievestream, and the estimated gift-sending value of the HB model at that same time step, and averaged overall values. *RMSE* is the standard deviation of the average of squared differences between the estimated gift-sending value and actual gift-sending value at time step t. We compute the *MAE* and *RMSE* across all 13 trials for the HB model and compare the differences. The results are reported in Table 6. Details of the cross-validation *MAE* and *RMSE* are small. As mentioned previously, we perform a log transformation for the variable of gift giving. We use the exponential of the *RMSE* value to restore it to RMB. As shown in Table 6, the *RMSE* value of the first trial is 3.23, so the exponential is 25.27 RMB. This shows that our prediction error of the viewers' gift-sending value in the 13th live stream is 25.27 RMB.

Table 6 *MAE* and *RMSE* for the HB Model

Index	1	2	3	4	5	6	7	8	9	10	11	12	13	Average
MAE	2.00	1.46	1.58	1.41	1.84	1.13	0.81	1.48	0.66	1.01	0.68	1.12	2.18	1.33
RMSE	3.23	3.02	2.01	1.42	2.12	2.37	1.53	1.83	0.86	1.02	0.98	2.75	2.56	1.98
F ratio	0.84	0.63	0.64	0.56	0.47	0.46	0.29	0.59	0.60	0.49	0.32	0.74	0.75	0.57

Furthermore, to test the HB model's prediction performance, we set the null model to assume the mean of the gift-sending value that the viewers paid $(\bar{Y}_j)$ every second as the predicted value estimated by the HB model (in the training set). As shown in Equation 3, we use the holdout data (the 13 streams in each trial) to calculate the sum of the squared differences between the actual gift-sending values (Y_j) and the estimated gift-sending values $(\hat{Y}_j)$ at a given interval and use it as the numerator. Then, we calculate the sum of the squared differences between the actual gift-sending values (Y_j) and the mean of the gift-sending values $(\bar{Y}_j)$ at a given interval and use it as the denominator. We divide these two formulas and use an *F* test to test the hypothesis.

H_0: the null hypothesis means that the prediction error of the gift-sending value of the HB model is the same as or worse than the null model.

H_1: the opposite hypothesis is that the prediction error of the gift-sending value of the HB model is smaller than that of the null model.

$$H_0\text{: } \frac{\sigma_1^2}{\sigma_2^2} \geq 1$$

$$H_1\text{: } \frac{\sigma_1^2}{\sigma_2^2} < 1$$

$$F = \frac{\sum_{j=1}^{n}\left(Y_j - \hat{Y}_j\right)^2 / v_1}{\sum_{j=1}^{n}(Y_j - \bar{Y}_j)^2 / v_2} \sim F(v_1, v_2), \tag{3}$$

where *j* refers to the predicted give-gifting value in each live stream. v_1 is the degree of freedom and refers to the total sample number of the 13 live streams, minus the number of estimated parameters in this study (there were 13 parameters in this study). v_2 is the degree of freedom and refers to the total sample number of the 13 live streams minus one.

As shown in Table 6, all *F* ratios are less than one at the significance level of $p < 0.01$. The results show that the HB model has satisfying predictive performance.

7. Conclusions and Implications

7.1 Conclusions and Discussions

This study applies the HB model to develop a predictive streamers' revenue statistics model and examine the effects of comment metrics, discrete emotional comments, and streamers' marketing strategies on viewers' gift-sending behavior and the cross-level effects of streamer heterogeneity. We find that the effects of viewers' comment features and streamers' marketing strategies on viewers' gift-sending behavior depend on the streamer heterogeneity. Specifically, the more a male streamer chats with the viewers, the higher the viewers' gift-sending behavior. Second, the streamers with higher outward beauty receive more excited comments, and the more they chat with and responded to the viewers, the higher the viewers' gift-sending behavior. Third, sociable streamers receive more total, negative, and complaining comments, and the more they respond to the viewers' questions and share food features, the higher the viewers' gift-sending behavior. A persuasive streamer has more praising comments, and the more they share food features, the higher the viewers' gift-sending behavior. Further, a comical streamer has more excited, praising, complaining, disappointed, and ridiculing comments, and the more she/he chat with the viewers, the higher the viewers' gift-sending behavior.

Past studies on gift-sending behavior in live streaming have pointed out that comments related to excitement (Zhou et al., 2019) and the interaction between the streamer and the viewer (Yu et al., 2018) positively affect the gift-sending behavior of viewers. Similar research has also indicated that the characteristics of the streamer (such as personalization, sociability, and attractiveness) also positively affect the viewers' intentions to send gifts (Wan et al., 2017; Wohn and Freeman, 2020). Nevertheless, these past studies neglect that there may be an interaction effect between the variables mentioned above, which would lead to biased conclusions. This study proves that streamer heterogeneity has cross-level effects on the relationships between the viewers' comment metrics and viewers' gift-sending behavior; between the viewers' discrete emotions and viewers' gift-sending behavior; between streamers' behaviors and viewers' gift-sending behavior. The conclusions of this study can help live-streaming platforms better understand the factors that affect the viewers' gift-sending behavior.

Further, prior studies have discussed paid gifts from the perspectives of social psychology, such as social interaction (Yu et al., 2018; Zhou et al., 2019), attachment (Wan et al., 2017), emotion (Phonthanukitithaworn and Sellitto, 2017), attractiveness (Wohn and Freeman, 2019), and reciprocity (Zhang et al., 2019). Our study is the first to synthesize an analysis of paid gifting behavior in live streaming from the perspectives of viewers' various comment metrics, discrete emotion-embedded comments, and streamers' characteristics and behaviors. This study contributes to the literature by demonstrating that the effects of different comment metrics and discrete emotions on gift-sending behavior in live streaming depend on streamer heterogeneity.

In addition, Zhou et al. (2019) examine viewers' comments and gift-sending behavior using a fixed period (one minute) as an analysis unit is not reasonable. Because the viewers' behaviors are affected by streamers' behavior, and viewers' behavior is the result of their considerations, a viewer's behavior will have a carryover effect. Therefore, Zhou et al. (2019) research can not identify the distribution patterns hidden in streamer behaviors and gift-sending behavior, possibly causing measurement errors. This study corrects the analysis unit of time to precisely explore the viewers' comments and gift sending to identify effectively that the true distribution patterns of their behaviors depend on streamers' behaviors. Furthermore, past studies related to gift sending have only counted the number of gifts (Zhou et al., 2019), ignoring the unequal value of each gift, which in turn have caused measurement errors. Since DouYu offers many types of gifts, and the value of each gift differs, this study revises the coding of the gift values according to the gift values provided on the DouYu website.

Furthermore, most previous studies have employed self-reporting methodology (i.e., survey questionnaires and in-depth interviews) to survey streamer revenue (Wan et al., 2017; Wohn and Freeman, 2020; Zhang et al., 2019). This study adopts the following two approaches for data collection. First, it employs data crawling to examine the data on gift sending and second-by-second chat records from DouYu. Second, we conduct content analysis to gather information on streamers' behaviors. Both approaches produce abundant data on viewers and streamers and thus facilitate more accurate model results. These data sources also strengthen the internal validity and model accuracy.

Finally, prior studies of paid gifting in live streaming have used regression (Yu et al., 2018; Zhou et al., 2019), structural equation modeling (Phonthanukitithaworn and Sellitto, 2017; Wan et al., 2017), and content analysis (Zhang et al., 2019). This study contributes to the literature on streamer revenue forecasting in live-streaming platforms by proposing an HB model that captures streamer heterogeneity. Another advantage of the applied HB model is that we can solve the problem of insufficient sample information and provide better forecasting accuracy.

7.2 Theoretical Implications

From a theoretical perspective, the contributions of this research are twofold. First, we contribute to the literature on the emerging social media of live streaming by focusing on a novel function called paid gifting. Currently, only a few studies on live streaming have focused on the real behavior of paid gifting, and most of the prior live-streaming studies have used the perspective of social psychology. Our study is the first to synthesize an analysis of paid gifting behavior in live streaming from the perspectives of viewers' comment metrics, discrete emotion-embedded comments, and streamer behavior and heterogeneity. This study contributes to the literature by demonstrating that the effects of comment metrics, discrete emotion-embedded comments, and streamers' behaviors on viewers' gift-sending behavior in live streaming are dependent on streamer heterogeneity. More importantly, this study proves that the conclusions of prior live-streaming studies may be biased because they ignore the impacts of streamer heterogeneity (e.g., physical attractiveness, gender, and streamers' hosting styles).

7.3 Managerial Implications

From a managerial perspective, the purpose of this study is to construct the streamer revenue forecasting model and examine the effects of viewers' comment metrics, discrete emotional comments, and streamers' characteristics and marketing strategies on gift-sending behavior in live streaming. The empirical illustrations support the prediction accuracy of the HB model we propose. Further, the effects of comment metrics, discrete emotional features, and streamer behavior have implications for live-streaming platforms in their marketing decision making.

More importantly, they need to reconcile streamer heterogeneity to provide the ideal live-streaming marketing strategy. In other words, there is no "one size fits all" solution to live-streaming marketing; its implementation depends on streamers' personal traits. A male streamer could focus on chatting with the viewers. A streamer with higher outward beauty would need to focus on chatting with the viewers, responding to viewers' questions, and keeping viewers excited. A sociable streamer could focus on responding to the viewers' questions, showing the cooking process, and stimulating the viewers to leave a message even if the message is negative. A persuasive streamer could share food features and try to elicit viewers' praise. A comical streamer could encourage the viewers to leave messages whether the message is positive or negative and continue to chat with the viewers. Furthermore, to avoid measurement errors, this study suggests that the marketer should precisely correct the coding of the viewers' comments and gift-sending variables based on the streamer behavior and gift values confirmed by the live streaming platform.

7.4 Limitations and Future Research

There are a number of avenues for future work to extend the proposed HB model in live-streaming marketing. First, in practice, the normal distribution used in this study may not be appropriate to some live-streaming contexts and may need to be relaxed. The normal distribution implies a symmetrical relationship, which may be overly restrictive in some live-streaming environments. Second, in reality, the forms of live streaming on various Internet or mobile platforms (e.g., Facebook, YY platform, YouTube, and Twitch) are diverse, which may produce different effects on revenue. This study suggests that future research needs to consider the effects of the heterogeneity of different live-streaming platforms on streamer revenues. Similarly, research on live-streaming revenue will be affected by heterogeneity in different product types (e.g., food, sports, games). Future research can also investigate the impact of the heterogeneity of varying product types. Third, as the number of viewers increases or decreases over time during a live stream, if the prediction takes place before or at the start of the live stream, the number of viewers cannot be included as a predictor. This study recommends that future scholars who adopt a purely predictive approach include the number of viewers appearing at time t during the live stream to predict the streamer's final revenue. Even more useful is the time series of the number of viewers from the start of the live stream until time t and the revenue curve until time t. In addition, it should be noted that the predictive models for streamer revenue cannot provide direct causal explanations.

Appendix: Virtual Gift Design on Douyu Live-Streaming Platforms

Gift Value	Gift Name
Free	Fish Ball
Cheap (<¥10)	Weak chicken, Fish Ball, Like, Ha Ha, Light Stick, Small Flying Saucer, Tanabata Gift-Firework Rain, Tanabata Gift-Smoke Bouquet, etc.
Medium (¥11~¥100)	Bank Card
Expensive (¥101~¥500)	Airplane, Golden Carriage, Tanabata Gifts-Fireworks Praise, etc.
Extravagant (>¥501)	Super Rocket, Castle, Rocket, Aircraft Carrier, etc.

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