7-8-2023

Driving Live Streaming Commitment with Goal Incentives Based on Viewer Reciprocity: A Quasi-Natural Experiment

Zhe JING
The Hong Kong Polytechnic University, joe-zhe.jing@connect.polyu.hk

Jack Tong
Nanyang Technological University, jack.tong@ntu.edu.sg

yue guo
Southern University of Science and Technology, guoy@sustech.edu.cn

Alain Chong
University of Nottingham, alain.chong@nottingham.edu.cn

Driving Live Streaming Commitment with Goal Incentives Based on Viewer Reciprocity: A Quasi-Natural Experiment

Completed Research Paper

Zhe Jing
The Hong Kong Polytechnic University
Hong Kong, China
Southern University of Science and Technology
Shenzhen, China
joe-zhe.jing@connect.polyu.hk

Jack Tong
Nanyang Technological University
Singapore
jack.tong@ntu.edu.sg

Yue Guo
Southern University of Science and Technology
Shenzhen, China
guoy@sustech.edu.cn

Alain Chong
University of Nottingham
Ningbo, China
alain.chong@nottingham.edu.cn

Abstract

Driving streaming commitment from individual streamers is critical to the sustainable growth of live streaming platforms, and platform operators tend to apply incentives to motivate streamers for such voluntary content contributions. However, most monetary incentives have an unintended impact on reducing the intrinsic motivation of streamers, resulting in fewer efforts and less commitment to streaming productions. This study explores the effect of a novel goal incentive design based on viewer reciprocal support. Leveraging a quasi-natural experiment, we estimate the causal impact of the incentive scheme using the combination of a coarsened exact matching (CEM) approach with the difference-in-differences (DID) model. Our results confirm that the goal incentive based on viewer reciprocal support could positively drive streamers' efforts in live streaming. This paper contributes to the literature on driving user generated content in emerging digital platforms and offers important implications for streaming platform operators.

Keywords: Live Streaming, User Generated Content, Platform Incentive Design, Quasi-Natural Experiment, Streaming Motives

Introduction

In recent years, live digital streaming services (e.g., Twitch and TikTok) have grown exponentially, and viewers spent more than 548.7 billion hours watching streaming content in 2021 (Statista, 2022). Live streaming is the process of recording and broadcasting content simultaneously over the internet in real-time, setting it apart from non-live media such as vlogs. Live streamers are individuals who broadcast themselves while playing games, performing music, and engaging in numerous other activities on various platforms to connect with friends and fans. They play a vital role in the growth of the live streaming platforms. Most platforms rely on individual streamers' voluntary production of content to increase viewer engagement and support platform growth. For example, Twitch, the leading live streaming platform for video games in the U.S., has more than 7.5 million streamers whose content is being viewed over 24 billion hours in 2021 (Yuen, 2022). Living streaming platforms make money by collecting a portion of funds used to purchase digital products that viewers use to send to streamers. The platforms hope the streamers contribute more excellent content and more viewers purchase virtual goods to encourage their favorite streamers. Therefore, these platforms use a variety of incentive schemes to motivate streamers' active participation in streaming content creation (Hukal et al., 2020), the most common of which is financial compensation. For example, YouTube established a $100 million fund to reward the best producers of the month who continuously create popular short videos (Southern, 2021).

However, numerous studies have demonstrated that monetary incentives can adversely affect users' performance (Goes et al., 2016; Gneezy & Rustichini, 2000; Frey, 1994). The main reason is that the intrinsic desire to commit efforts can be affected by monetary incentives. According to self-perception theory, individuals observe their contribution and conclude that they must be somewhat altruistic (Qiao et al., 2021). When the platforms initiate some monetary incentive scheme, the users focus more on the incentives, not on the altruism, which leads them to reduce their efforts and produce less valuable and lower quality content if they adopt an effort-to-incentive attitude (Heyman & Ariely, 2004; Burtch et al., 2018). Such an unintended undermining effect would be more pronounced for live streaming content contribution because it requires streamers to have a higher intrinsic motivation to produce interactive and engaging streaming content (Friedlander, 2017).

Leveraging the interactive communication and social features of live streaming, platform managers could design an innovative incentive scheme based on goal attainment of viewers' reciprocal support to drive streamers' efforts on content contribution. This goal attainment incentive combines the advantage of traditional incentive awards and peer reciprocal support. First, it incentives streamers to take more streaming efforts to attain the goal with monetary benefits (Cabral and Li, 2015; Burtch et al., 2018). Second, to attain the incentive, streamers need to engage viewers to gain their reciprocal support through gifting and tipping (i.e, peer award) (Burtch et al., 2021; Frey and Gallus, 2017). Third, the achievement of the incentive not only brings monetary value to streamers, but also facilitates them to gain symbolic status relative to other streamers as the scheme is designed with various goal settings (Gallus, 2017; Kosfeld and Neckermann, 2011).

Yet, there is a dearth of empirical effort to understand the potential impact of such goal attainment incentive on streamers' commitment in live streaming. While there has been some research on the impact of monetary and goal incentives on individual productivity in digital platforms like online communities and social media, there has been limited focus on live streaming platforms, which differ from traditional non-live media. It's worth noting that monetary incentives can influence both the streamers' altruistic contributions and the viewers' rewarding behaviors, which is the major incoming for the live streaming platform. In particular, extant studies provided limited insights into how the goal attainment of viewer reciprocal support might alter streamers' efforts in producing high quality streaming content to engage viewers. On the one hand, the goal to attain viewer reciprocal support might motivate streamers to produce more attractive content for viewer interactions, leading to higher motivation for better viewer engagement streaming; on the other hand, the incentive of the goal might induce streamers with mindset to nudge and push viewers for reciprocal support, resulting in lower level of motivation in streaming and poorer viewer experience. To fill this literature and empirical gap, we address the following research questions:

1. Does the goal attainment incentive based on viewer reciprocal support motivate streamers for higher streaming effort commitment?

2. How does the incentive scheme affect the viewer engagement in the streaming?

3. How do the effects of goal incentive vary across different streamers?

To evaluate these questions, we collaborated with the data science team of a leading streaming platform in Asia to acquire a proprietary dataset, which includes a random selection of over 15,000 live streamers during the launch of a goal attainment incentive program that award streamers to attract viewers' gifting behaviors. The streaming platform hosts more than 1.6 million individual streamers for live streaming with a spectrum of e-sports commentary, entertainment (e.g., music and dance), talent shows, and outdoor activities. To motivate individual streamers for more streaming activities, the platform designed and implemented a goal attainment incentive program in the mid of November 2019 that lasted to the end of

December 2019. This incentive program was open for voluntary enrollment across the platform and it was designed to motivate streamers to produce more engaging content for viewers' gifting. The incentive scheme was based on the number of gifts and virtual amount a streamer received during the live streaming on daily basis. There were five tiers of the goal and each tier was set up to be an independent task for streamers. Streamers needed to attain a specific number of gifts from viewers to complete each tier and higher tier was designed with higher required number of gifts. The incentive scheme was a week-long program and was automatically renewed on every Sunday at 12:00am with the past progress cleared off. Streamers would receive virtual reward from the platform at the following week based on the total number of goal tiers completed in the prior week. There would be no virtual reward if the streamer failed to complete any tier in the week. The datasets contain detailed record for streamers' streaming activities and viewer interactions within each streaming session for 68 days (25 days before the launch of this incentive program and 43 days after the launch).

Our identification strategy hinged on streamers' voluntary participation for the newly launched incentive program in the first week: the treatment group consisted of streamers who voluntarily enrolled into the incentive program since the first week of the program launch, and control group were streamers who never enrolled into the program during our observation period. Fully aware of the potential self-selection issue of streamer participation, we took the following efforts to address the endogenous concerns. First, we applied a widely applied non-parametric matching approach of Coarsened Exact Matching (CEM) (Ge et al., 2021; He et al., 2021) to relieve the imbalance between the treatment and control groups (i.e., alleviated self-selection). Our matching practice verified that the matched sample in the treatment and control groups presented similar characteristics. Second, leveraging the cross-sectional time series nature of our data, we adopted a Difference-in-Difference (DID) model on the matched sample with two-way fixed effects (streamer fixed effects and the daily fixed effects), to further account for unobserved time-invariant individual specific variables and temporal effects (i.e., accounted for unobservable).

Our analyses yielded several interesting findings. First, the goal attainment incentive program could motivate individual streamers to devote more streaming efforts. Streamers participated in the incentive program carried out 37.7% longer live streaming per session and streamed 17.0% more sessions than those of streamers in the control group. Second, our empirical dataset empowered us to generate a rich set of user engagement measurements. Analyses results demonstrated that streamers in the incentive program conducted more engaging live streaming content measured by viewers' viewing length, number of viewers, interactive comments, and gifting behaviors. Specifically, there were 123.4% more viewers per session, and viewers spent 2.1% longer time, sent 19.1% more interactive comments per viewer, and 9.1% more viewers sent virtual gift with an average of 2.9% higher in value for streamers who participated in the program relative to those in the control group.

This work carries important contributions to the academic literature and to practice. First, it contributes to the IS literature on user content generation. While past research has primarily focused on the text-based content generation of user review and feedback with limited audience interactions (Burtch et al., 2018; Huang et al., 2016; Burtch et al., 2021), our study provides a pioneering effort in understanding streamers' efforts in producing live streaming video content, which provides more dynamic and interactive elements of audience engagement. Second, we also advance the knowledge in exploring the effect of a novel type of goal attainment incentive scheme based on viewers' reciprocal support, which is different from conventional monetary or status reward purely based on user generation efforts (Huang et al., 2019; Goes et al., 2016; Chen et al., 2019). Third, this study brings a new research perspective in the nascent stream of research in live streaming. While most studies look into features that might engage viewers in live streaming, we tackle the challenge of motivate streamers for streaming commitment. Furthermore, we also offer managerial insights to understand the effectiveness of performance-based incentive on driving streamers' motivation on streaming activities. Motivating content creators for continuous production and participation is critical for streaming marketplaces (e.g., Youtbue, Twitch, and TikTok etc.) and many platforms offer rewards as a direct intervention. However, monetary reward might be detrimental for the intrinsic motivation of streamers who enjoy the social interaction and recognition through live streaming. Thus, platform managers need to design a more appropriate incentive scheme to retain the motivation of streamers. Our empirical findings demonstrate that a goal attainment incentive schemes not only attract streamers to invest more efforts in producing live streaming, it also motivate them to generate live streaming with higher viewer engagement.

Literature review

User Content Generation in social platform

The development of information technology systems has facilitated the prevalence of user content generation (UGC). Specifically, UGC is a critical component of online shopping and it has been long considered as a complementary channel to signal quality and reduce information asymmetries (Forman et al., 2008). Indeed, there is a rich body of literature in IS and marketing documenting the positive effect of UGC review volume and rating on customer choice and purchase (Vana and Lambrecht, 2021; Mudambi and Schuff, 2010; Li and Hitt, 2008). Voluntarily shared purchase experience and product review assist shoppers to attain useful product information and boost their purchase confidence. For instance, a higher average rating usually sends a positive signal of product quality and higher review volume suggests that the product is in high demand and popularity (Wu et al., 2015).

Moreover, the rise of online communities presents another format of online user engagement of knowledge contribution and content creation. Different from UGC on e-Commerce sites, user contributed information composes the primary content of the online communities (Sun and Zhu, 2013; Susarla et al., 2012). For example, Wikipedia leverages knowledge contribution of individual users to grow the content supply and Reddit hosts various interesting and trendy topics posted by individuals. A nascent but growing stream of research has explored how the quality and novelty of the content might engage audience (Wang et al., 2021; Burtch et al., 2021). Nevertheless, most extant efforts have been invested in text-based UGC and little is known about UGC in live streaming (Gros et al., 2017).

In comparison to other forms of user-generated content, such as product reviews (e.g., Tripadvisor reviews) and knowledge sharing (e.g., Wikipedia), live streaming content possesses numerous distinct properties that enable streamers to maintain a higher level of intrinsic motivation (as summarized in tab:distinct). First, in contrast to product reviews and knowledge sharing, where content creators typically reveal little personal information (i.e., pseudonymous identity), live streaming streamers share numerous aspects of their social identity with viewers, such as gender, appearance, and occupation, resulting in increased levels of social recognition. Second, unlike other types of content, live streaming encourages users to follow the streamer and engage in peer interaction while watching, thereby establishing a social connection. Thirdly, in comparison to other forms of user-generated content, live streaming offers a high level of involvement for dialogue and engagement, which makes the streaming experience entertaining for both streamers and watchers. As a result, the majority of streamers offer content on a consistent basis for the sake of entertainment, social recognition, and connection (Törhönen et al., 2019; Bründl and Hess, 2016; Scheibe et al., 2016).

UGC Type	Live Streaming	Review Comment	Knowledge Sharing
Identity Transparency	High	Low	Low
Social Connection	High	Low	Low
Interactivity	High	Low	Low

Table 1. Distinct Features of Live Streaming Content Contribution

We contribute to the current literature of UGC by looking into the emerging format of live streaming. First, we directly answer to the question of motivating individual streamers for active streaming productions, which is critical to the success of streaming platforms. In addition, extending extant studies looking the quality of UGC with limited measurements in diagnostic and usefulness, this research provides a rich set of dimension to understand live streaming content for viewer engagement in terms of viewing length, communications, and gifting behaviors.

Platform Incentives for UGC

An extensive stream of literature has explored effects of reward in driving the motivation of UGC. Generally speaking, these rewards could be categorized into monetary and non-monetary incentives (Wang et al., 2021; Gallus, 2017, Liu and Feng, 2021). Traditional agency theory suggests that momentary incentives can induce more user efforts, and there is a great deal of studies document such positive impact on UGC. For example, Cabral and Li (2015) found that an incentive rebate stimulated higher volume of reviews and the reward led to more positive feedback. Wang et al. (2021) concluded that a monetary incentive could have a spillover effect on the free content contribution. Nevertheless, a lengthy research also documented that monetary incentive might crowd out the intrinsic motivation of individual's efforts (Deci et al., 1999; Ariely et al., 2009; Gneezy et al., 2011). This is particularly true for UGC because most users actively participate in UGC because of intrinsic motivations such as altruism, personal enjoyment, recognition, and reputation building (Wasko and Faraj, 2005; Sun et al., 2017; Pu et al., 2020; Qiu and Kumar, 2017). Goes et al. (2016) documented that users' motivation of content contribution decreased dramatically after attaining the incentive.

To alleviate the unintended effect of momentary incentives on users' intrinsic motivation, scholars has investigated the combination of reward with other social recognition schemes. For instance, Burtch et al. (2018) combined social norm and financial incentives to drive both the quality and quantity of UGC. Furthermore, Zhang and Zhu (2011) demonstrated that audience size had a positive relationship with users' motivation for knowledge contribution. In addition, studies also looked into other types of intervention that might affect the motivation of UGC. For example, Burtch et al. (2021) designed a field experiment to gauge the impact of peer reward on the volume and novelty of UGC. Gallus (2017) explored that a pure symbolic reward had positive impact on voluntary content contribution. Huang et al. (2019) found that a performance feedback could positively affect user content creation.

Extending this line of research, we study the effect of a novel goal attainment incentive with a combination of monetary incentive, peer reciprocal support, and symbolic status, which could be applied in the UGC context when social interaction and engagement is high. Our empirical results suggest that such incentive scheme not only motivates streamers with more streaming commitments, but also drives the streaming quality with better viewer engagement. Additionally, we also demonstrate that the hierarchical design could further motivate streamers who successfully attained higher level in the prior day.

Live Streaming

Live streaming, as a new type of content sharing and social interaction, has attracted great attention from academic scholars. A growing body of research studied the motives for streaming production (Hilvert-Bruce et al., 2018; Friedlander, 2017; Fietkiewicz et al., 2018). For instance, Zhao et al. (2018) investigated different motivational factors driving live streamers' continuous broadcasting commitment from a self-determination theory perspective. They found that both intrinsic motivation (e.g., challenge seeking, task enjoyment and desire for self-presentation) and extrinsic motivation (e.g., anticipated extrinsic reward, self-esteem benefits, social benefits and feedback) significantly influenced live streamers' performance expectancy. Furthermore, Bründl and Hess (2016) concluded that while the volume of content contribution on social live streaming platforms was mainly driven by individual motives, the commitment of long-term streaming production was primarily affected by a streamer's social capital embedded among relationships with their followers. Similarly, Lu et al. (2018) reported that social needs is a primary motive for streaming activities, and most streamers post streaming to share their life with others, demonstrate their talents, and make more friends.

Another stream of literature focused on understanding the feature designs in drive viewer engagement and interactions. In particular, Hu et al. (2017) exhibited that both streamers' identification and group identification could positively lift viewers' intention to watch a streaming session. Lin et al. (2021) studied how streamers' emotion expression might affect viewership and gifting behaviors. They found that a happier streamer in live streaming could induce more tipping activities. In addition, Lu et al. (2021) showed the positive relationship between viewer size and viewer gifting activities. Zhao et al. (2019) revealed that category switching could benefits incumbent streamers with larger view inflow.

While there has been some research on the impact of monetary and goal incentives on individual productivity in digital platforms like online communities and social media, there has been limited focus on live streaming platforms, which differ from traditional non-live media. It's worth noting that monetary incentives can influence both the streamers' altruistic contributions and the viewers' rewarding behaviors, which is the major incoming for the live streaming platform.

This work advances the knowledge of live streaming by examining how a goal attainment incentive could drive streamers' commitment in live streaming. In addition, we also provide empirical evidence that such incentive program would induce higher quality of streaming content as measured by number of viewers, viewing length, viewer communications, and gifting behaviors.

Empirical Context

Company Background

The company partner (who prefers to remain anonymous) is a large live streaming platform in China that was founded in 2016. The platform hosted individual streamers to stream live content covering e-sports commentary, music and dance, talent shows, and outdoor activities, different with the live streaming shopping. Individual streamers can broadcast live streaming shows in their live streaming room, each of which has a unique ID. Streamers had diverse commitment for streaming content and a typical live streaming show could last between a couple of minutes to over several hours (e.g., professional streamers who make a living on the platform may live stream several hours a day). The platform experienced exponential growth since its inception, by 2021, the company has attracted around 1.6 million individual streamers and over 130 million monthly active users. Viewers can enter and exit any live streaming room at any time during the live streaming session, and they can also share their opinion and communicate with peer viewers through the flying-comment feature. In addition, viewers can send virtual gifts in live streaming shows to show appreciation and support to the streamer.

Goal Attainment Incentive Program

Despite the phenomenal development, the platform faced increased challenge in retaining existing streamers to actively produce live streaming content. Indeed, majority of individual streamers started to do live streaming because of intrinsic motivation for enjoyment and social recognition. However, they might soon lose interest because live streaming requires high commitment of continuous efforts, and many of individual streamers might receive very few attentions from viewers. Therefore, the platform needed to implement an appropriate incentive program to keep these individual streamers motivated for live streaming.

On 18th, November 2019, the platform launched a goal attainment incentive program based on the reception of viewer virtual gifting and the program enrollment notice was sent to all streamers one week earlier through in-platform message for voluntary participation. The enrollment ended on 17th, November and all participated streamers would automatically started the incentive challenge starting at 0:01am on 18th, November. At the pilot stage (the first 6 weeks), streamers were automatically enrolled in each incentive cycle but unanticipated streamers could not enroll into it. Viewers would see an icon at the right bottom of the live streaming session if the streamer participated in this program.

The program was designed to encourage casual individual streamers to actively produce live streaming and engage viewers for gifting interactions. The goal attainment task was operated on daily basis with a cycle of 7 days and every cycle started at 0:01 am on each Monday. The incentive goal was set with 5 tiers and each of which had independent objectives (in terms of minimum number of viewers sent gifts and minimum total virtual value of these gifts) for streamers to complete in order to complete as summarized in Table 2. The streamer would obtain a specific number of star(s) once completing the designated tier of goal and the number of stars could be accumulated within an incentive cycle (e.g., from Monday to Sunday). The platform would offer the streamer virtual reward (that could be redeemed for monetary value) based on the number of stars she obtained in the prior incentive cycle, and more stars would convert to higher monetary incentive offered by the platform. Due to commercial confidentiality, the platform could not share with us the detailed breakdown of the monetary incentive value corresponding to each star the streamer attained during the program, but the value of monetary incentives is monotonic to the number of stars.

Goal Attainment	First Tier (1 Star)	Second Tier (2 Stars)	Third Tier (3 Stars)	Fourth Tier (4 Stars)	Fifth Tier (5 Stars)
Number of Viewers Sent Gift	3	5	8	10	30
Virtual Value of Gifts	200	1,000	2,000	6,000	10,000

Table 2. Incentive Tiers

Data

We worked with the data analytic team to acquire a proprietary data set from a random sample of 15,875 streamers on the platform. The data extraction covered from 25 October, 2019 (25 days before the launch of the program) to 31 December, 2019 (the end date of the pilot stage). Our data contained granular records of streamers' streaming activities and viewers' interactions (i.e., watching length, comment and gifting behaviors) during each streaming session. In particular, for each streamer, our data had records for the time stamp when the streaming session started and ended. Furthermore, within each streaming session, we observed each viewer's entry and exit timestamp, the communication comment, and whether they sent a virtual gift. If viewer sent a virtual gift, the dataset also took note of both the virtual and monetary value of the gift. In addition, we obtained the background information of each streamer in terms of gender, union membership, and streaming category.

To organize the data records into a panel structure, we took the following steps. First, we counted the total number of streaming sessions and average length of each streaming session per streamer on daily basis. Second, we identified each viewer's entry to the streaming session and calculated the total number of viewers per live streaming session per streamer every day. Third, we recorded all viewing engagement activities of each viewer within each session, which is operationalized as the viewing time, the number of communication comments, number of gifts and the value of each gift sent. Fourth, we aggregated viewers' activities on individual session level by calculating the average viewing length, the total number of viewers, number of communication comments, and number of gifts for each streaming show. Fifth, we further aggregated our measurements at the streamer daily level with the average viewing length, average number of viewers, and the average number of communication comments and gifts received per streamer across all sessions each day. For a detailed list of variables, see Table 3.

Variables	Variable Definition
$Gender_i$	Indicator of gender(1: male; 0:female)
$Union_i$	1: streamer i joined a guild, 0 otherwise
Age_i	Age of streamer
$StreamingLen_{it}$	The length of streamer(i)'s streaming on date(t) (in hours)
$Streamingtimes_{it}$	The times of streamer(i)'s streaming on date(t)
$AvgViewLen_{it}$	Average length of every viewer stay in the room of streamer(i) (minutes)
$UniqueViewers_{it}$	The number of total unique audience of streamer(i) on date(t)
$Comments_{it}$	Average number of comments left for streamer(i) on date(t)
$GiftValue_{it}$	The average value of gift sent to streamer(i) on date (t) by per viewer
$UniquePayViewersi_t$	The number of viewers who spend money on streamer(i)on date(t)
$FollowersAdd_{it}$	The number of new followers added compared to date(t-1) for streamer(i) in date(t)
$FollowNum_{it}$	The number of of followers
$StarLevelFinished_{it}$	The levels of streamer(i) finished on date(t)
$PostLaunch_t$	Binary time indicator for the time after the launch program
$TreatGroup_i$	Indicator for streamers who participated in the program

Table 3. Variable List

Identification Strategy

Our treatment group consisted of streamers who enrolled to the incentive program at the pilot stage and the control group were streamers who did not participate in the incentive program. Ideally, we would like to estimate the effect of the incentive on streamers' streaming efforts and quality by comparing the differences between the treated and control groups across the period before and after the launch of the incentive program with a difference-in-differences (DID) approach (Huang et al., 2016; Zhang et al., 2021). However, there would be endogeneity concerns over the internal validity of the DID method in our empirical context because individual streamers endogenously made the decision to participate this incentive program. In this way, the treatment and control groups might not satisfy the parallel trend assumption across our focal outcome variables.

Variables	mean	sd	min	max
$Gender_i$	0.274	0.446	0	1
$Union_i$	0.221	0.415	0	1
Age_i	26.89	6.778	19	76
$StreamingLenth_{it}$	1.356	2.765	0	24
$StreamingTimes_{it}$	0.578	1.088	0	41
$AvgViewLen_{it}$	0.0577	0.844	0	194.8
$UniqueViewers_{it}$	46.49	760.4	0	171552
$Comments_{it}$	1.430	7.701	0	687
$GiftValue_{it}$	0.0643	1.008	0	250
$UniquePayViewers_{it}$	0.176	2.214	0	416
$FollowersAdd_{it}$	0.861	29.78	0	5414
$FollowNum_{it}$	1172	7041	0	254815
$StarLevelFinished_{it}$	0.00549	0.108	0	5
$PostTreat_t$	0.632	0.482	0	1
$Treat_i$	0.50	0.5	0	1

Table 4. Descriptive statistics of variables

To mitigate the endogeneity concern, we applied Coarsened Exact Matching (CEM), a non-parametric matching approach that was recently introduced into empirical research in IS field (Ge et al., 2021; He et al., 2021). The results of our CEM method are summarized in Table 5. Noted that we had 3,620 streamers in the treatment group and 12,255 streamers in the control group before CEM, suggesting that around 22.8% of streamers on the platform participated the incentive program. These results were consistent with the overall participation rate of 23% provided by the platform management team. In addition, the units of the treatment and control groups differed significantly on selected key covariates in the pre-treatment period. In particular, units in the treatment group had a higher proportion of female streamers and union members. Streamers in the treatment group also demonstrated more streaming efforts and higher viewer engagement level than those in the control group in terms of longer streaming length, more streaming times, longer viewing length per session, more viewers per session, more communication comments posted by viewers and gifts during the streaming shows. The CEM procedure adjusted the imbalance between treatment and control groups, and generated a sample of 2,619 units in the treatment and control groups respectively that were indifferent from each other. Indeed, the t-test results showed that the matched units in the treatment and control groups are statistically indifferent across all key covariates.

Next, we estimated the causal effect of the goal attainment incentive on streamers' streaming efforts and quality by comparing the inter-temporal variations between matched individual streamers in the treatment and control groups applying the DID approach. To further address potential issues with omitted variables, we Incorporated individual streamers' fixed effects to account for streamer specific time-invariant unobservable variables, and we included daily fixed effects to control for unobserved strata-specific time trends. The specification of our DID model is:

$$S_{it} = \beta_0 + \beta_1 TreatmentGroup_i \times Post_t + \pi_i + \tau_t + \omega_{it} \quad (1)$$

where S_{it} represented a set of dependent variables measuring streaming efforts and quality for streamer i on day t. Specifically, we first estimated how the incentive program affected streamer's efforts in live streaming gauged by number of streaming sessions $\mathrm{StreamingTimes}_{it}$ and streaming length per session $StreamingLen_{it}$. Next, we explored how the incentive program might alter the streaming quality indicated by viewers' average viewing length (i.e., $\mathrm{AvgViewLen}_{it}$) as well as the number of viewers (i.e., $\mathrm{Viewers}_{it}$) and communication comments posted (i.e., $\mathrm{commentsit}_{it}$). It is plausible that high quality live streaming could retain more viewers to enjoy the content with longer viewing length and stimulate more peer communications. In addition, it is expected that viewers would send more gifts if they enjoyed the streaming content. Thus, we also estimated the effect of the incentive program on viewers' gifting behaviors measured by the total gift value and number of gifts. We included two way (streamer and day) fixed effects to account for the time-invariant differences across streamers with π_i and the unobserved temporal effect with τ_t. To deal with the potential auto-correlation within a streaming room, we clustered the standard error by streamers.

After Matching			
Variables	Treatment Group (n=3,620)	Control Group (n=12,255)	Unmatched t test p-value
Gender	0.311	0.252	0.000***
Age	26.832	26.757	0.556
Union	0.275	0.138	0.000***
Category1	0.079	0.077	0.708
Category2	0.058	0.079	0.000***
Category3	0.214	0.240	0.001***
Category4	0.550	0.506	0.000***
Category5	0.076	0.059	0.000***
Average streaming length	1.899	1.227	0.000***
Average streaming times	0.958	0.722	0.000***
Average viewing length	0.094	0.063	0.000***
Average number of audiences	126.65	39.711	0.012***
Average number of comments	1.710	1.54	0.000***
Average Value of gifts	0.143	0.082	0.000***
Average Number of audience paying gift	0.472	0.196	0.000***
After Matching			
Variables	Treatment Group (n=2,619)	Control Group (n=2,619)	Matched t test p-value
Gender	0.277	0.270	0.556
Age	26.867	26.918	0.787
Union	0.212	0.230	0.110
Category1	0.084	0.085	0.921
Category2	0.060	0.062	0.729
Category3	0.223	0.211	0.284
Category4	0.548	0.563	0.266
Category5	0.0583	0.051	0.275
Average streaming length	1.565	1.546	0.663
Average streaming times	0.843	0.830	0.468
Average viewing length	0.072	0.059	0.222
Average number of audiences	60.201	54.011	0.626
Average number of comments	1.730	1.768	0.714
Average Value of gifts	0.096	0.097	0.831
Average Number of audience paying gift	0.244	0.217	0.335

Notes: ***, ** and * indicate statistical significance at 1 % , 5 % and 10% respectively.

Table 5. CEM Balanced Check

Empirical Findings

Impact of Goal Attainment Incentive on Streamers' Live Streaming Efforts

As summarized in Table 6, the coefficients of the two-way interaction term are positive and statistically significant (p<0.01) in Columns (1) and (2), suggesting that the incentive motivated individual streamers to conduct longer live streaming per session. On average, streamers in the incentive program streamed 37.7% longer than those who did not participate the program as indicated by the coefficient value in Column (2). In addition, the positive and statistically significant coefficients of the interaction term in Columns (3) and (4) show that individual streamers participating the incentive program devoted more efforts in producing live streaming sessions. In general, streamers in the incentive program streamed 17.0% more sessions relative to those not in the program on daily level. These results demonstrate that the goal attainment incentive motivated streamers not only to invest more time for longer live streaming but also to devote efforts for more live streaming sessions.

	Streaming length	Log (Streaming length)	streaming times	Log (streaming times)
TreatedGroup*PostLaunch	0.996*** (0.016)	0.377*** (0.004)	0.297*** (0.007)	0.170*** (0.003)
Streamers	5,238	5,238	5,238	5,238
Observations	356,184	356,184	356,184	356,184
R-Squared	0.096	0.130	0.064	0.091
Individual Fixed Effects	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y

Notes: All results are based on OLS estimates from 5,238 streamers and 356,184 observations. Robust standard errors adjusted for clustering at the streamer level are provided in parentheses. All regression include individual and day fixed effects. ***, ** and * indicate statistical significance at 1 % , 5 % and 10% respectively.

Table 6. Impact on Streamers' Live Streaming Efforts

Impact of Goal Attainment Incentive on Streamers' Live Streaming Quality

Because of the interactivity nature, high engaging streaming could attain more viewers with longer viewing and more interactions. As such, we used the number of viewers, their viewing length, and communication activities during the live session to infer the viewer engagement in the streaming. Results are reported in Table 7. The positive and statistically significant coefficients of the interaction term in Columns (1) and (2) suggest that incentive program motivates streamers to generate live streaming that could attract more viewers per streaming session. In addition, the coefficients of the interaction term are positive and significant in Columns (3) and (4), showing that the streaming content will also attain viewers with longer viewing time per session for streamers who participated the incentive program. Next, the positive and significant coefficients of the interaction term in Columns (5) and (6) exhibit that after enrolling the incentive program, streamers produce live streaming that engage viewers with more communication comments per viewer. Thereby, these results indicate that the incentive program indeed drives streamers' motivation in generating higher engaging live streaming that attains more viewers, appeals longer viewing time, and attracts more communications among viewers.

	Viewing length	Log (Viewing length)	Number of viewers	Log (Number of viewers)	Number of comments	Log (Number of comments)
TreatedGroup* PostLaunch	1.703*** (0.005)	0.188*** (0.001)	2.246*** (4.405)	0.140*** (0.010)	2.246*** (0.050)	0.140*** (0.004)
Streamers	5,238	5,238	5,238	5,238	5,238	5,238
Observations	356,184	356,184	356,184	356,184	356,184	356,184
R-Squared	0.002	0.011	0.002	0.127	0.012	0.055
Individual Fixed Effects	Y	Y	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y	Y	Y

Notes: All results are based on OLS estimates from 5,238 streamers and 356,184 observations. Robust standard errors adjusted for clustering at the streamer level are provided in parentheses. All regression include individual and day fixed effects. ***, ** and * indicate statistical significance at 1 % , 5 % and 10% respectively.

Table 7. Impact on Streaming Quality (viewer engagement)

Furthermore, we also investigate whether the more engaging streaming content could translate into viewers' reciprocal support to help the streamer attain the incentive goal by sending virtual gifts. Results are summarized in Table 8. The positive and statistically significant ($p<0.01$) coefficients in Columns (1) and (2) suggest that viewers offer higher average value of gifts as they enjoy the streaming content from streamers in the incentive program. Moreover, the coefficients in Columns (3) and (4) are also statistically significant and positive, showing that more viewers would send gift form the streamer in the incentive program per live session. Taken together, our analyses provide empirical evidence that highly engaging live streaming indeed stimulates higher viewers' reciprocal support with larger value of gift and more viewers sent gift during the live session.

	Value of gifts	Log (Value of gifts)	Number of viewers	Log (Number of viewers
TreatedGroup*PostLaunch	0.074*** (0.007)	0.028*** (0.001)	0.222*** (0.010)	0.087*** (0.002)
Streamers	5,238	5,238	5,238	5,238
Observations	356,184	356,184	356,184	356,184
R-Squared	0.004	0.020	0.008	0.053
Individual Fixed Effects	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y

Notes: All results are based on OLS estimates from 5,238 streamers and 356,184 observations. Robust standard errors adjusted for clustering at the streamer level are provided in parentheses. All regression include individual and day fixed effects. ***, ** and * indicate statistical significance at 1 % , 5 % and 10% respectively.

Table 8. Impact on Streaming Quality (viewer gifting)

Prior Goal Attainment Amplifies the Incentive Effect

If the incentive program indeed drives up individual streamers' motivation on live streaming, we should expect that streamers who attained the challenge in the prior day would have higher motivation for streaming. Therefore, we explore how the challenge level achieved in the prior day would affect streamers' efforts in generating live streaming by constructing a difference-in-difference-indifferences(DDD) model with the following specification:

$$S_{il} = \beta_2 + \beta_{21}\,\mathrm{TreatmentGroup_i} \times Post_{\mathrm{t}} \times Challenge\ \mathrm{Level\ Completed}_{\mathrm{it-1}}$$
$$+\beta_{22} TreatedGroup_i \times Post_t + \gamma_i + \tau_t + \mu_{it} \qquad (2)$$

Results are reported in Table 9, 10, and 11. The positive and statistically significant coefficients of three-way interaction terms in Table 9 confirm that streamers who achieved higher tier in the prior day demonstrate higher efforts in live streaming in terms of streaming length and times in the following day. In addition, the positive and statistically significant coefficients of the three-way in Table 10 and Table 11 show that the streaming content has higher quality for streamers who attained higher tier in the prior day as it engages more viewers, attains longer viewing length, attracts more communication comments, and drives higher viewer reciprocal support with gifting.

	Streaming length	Log (Streaming length)	streamin g times	Log (streami ng times)
TG*Post_L*SLF(Continuous)	0.818***	0.261***	0.249***	0.128***
	(0.071)	(0.022)	(0.027)	(0.012)
TreatedGroup*Post_L	1.052***	0.343***	0.332***	0.180***
	(0.033)	(0.009)	(0.013)	(0.005)
Streamers	5,238	5,238	5,238	5,238
Observations	356,184	356,184	356,184	356,184
R-Squared	0.096	0.130	0.064	0.091
Individual Fixed Effects	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y

Notes: TG denote Treated Group; Post_L denotes PostLaunch; SLF denotes Star level finished. All results are based on OLS estimates from 5,238 streamers and 356,184 observations. Robust standard errors adjusted for clustering at the streamer level are provided in parentheses. All regression include individual and day fixed effects. ***, ** and * indicate statistical significance at 1 %, 5 % and 10% respectively.

Table 9. Effect of Prior Goal Attainment on Streamers' Live Streaming Efforts

	Viewing length	Log (Viewing length)	Number of viewers	Log (Number of viewers)	Number of comments	Log (Number of comments)
TG*Post_L*SLF(Continuous)	0.027**	0.019***	176.671***	0.891***	0.497***	0.166***
	(0.006)	(0.004)	(89.261)	(0.077)	(0.074)	(0.020)
TreatedGroup*Post_L	0.049***	0.025***	45.716***	0.890***	0.641***	0.178***
	(0.009)	(0.002)	(7.137)	(0.023)	(0.061)	(0.007)
Streamers	5,238	5,238	5,238	5,238	5,238	5,238
Observations	356,184	356,184	356,184	356,184	356,184	356,184
R-Squared	0.002	0.011	0.002	0.127	0.012	0.055
Individual Fixed Effects	Y	Y	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y	Y	Y

Notes: TG denote Treated Group; Post_L denotes PostLaunch; SLF denotes Star level finished. All results are based on OLS estimates from 5,238 streamers and 356,184 observations. Robust standard errors adjusted for clustering at the streamer level are provided in parentheses. All regression include individual and day fixed effects. ***, ** and * indicate statistical significance at 1 %, 5 % and 10% respectively.

Table 10. Effect of Prior Goal Attainment on Streamers' Live Streaming Efforts

	Value of gifts	Log (Value of gifts)	Number of viewers sending gift	Log (Number of viewers sending gift)
TG*Post_L*SLF(Continuous)	0.324***	0.117***	2.522***	0.384***
	(0.067)	(0.013)	(0.426)	(0.028)
TreatedGroup*Post_L	0.069***	0.033***	0.204***	0.102***
	(0.006)	(0.002)	(0.014)	(0.004)
Streamers	5,238	5,238	5,238	5,238
Observations	356,184	356,184	356,184	356,184
R-Squared	0.010	0.041	0.059	0.102
Individual Fixed Effects	Y	Y	Y	Y
Day Fixed Effects	Y	Y	Y	Y

Notes: TG denote Treated Group; Post_L denotes PostLaunch; SLF denotes Star level finished. All results are based on OLS estimates from 5,238 streamers and 356,184 observations. Robust standard errors adjusted for clustering at the streamer level are provided in parentheses. All regression include individual and day fixed effects. ***, ** and * indicate statistical significance at 1 %, 5 % and 10% respectively.

Table 11. Effect of Prior Goal Attainment on Streamers' Live Streaming Efforts

Discussions

Key Findings

In this work, we explored the causal impact of a goal attainment incentive program on streamers' streaming efforts and commitment on a live streaming platform. Leveraging the voluntary participation of individual sellers in this incentive program, we constructed treatment and control group using CEM and identified the casual impact with a DID approach. Our empirical results suggested that the incentive program could motivate individual streamers to devote more streaming efforts in terms of streaming length and streaming sessions. In addition, we also found that streamers in the incentive program would generate more engaging streaming content. Specifically, the live streaming content generated by streamers in the incentive program attracted more viewers, attained longer viewing, stimulated more viewer communication, and acquired higher gifting value. Furthermore, streamers' prior challenge completion moderated the positive effects of the incentive program since the identified effects were amplified for streamers who successfully completed higher tier of challenge in the prior day. Last but not least, we also documented a positive effect of the incentive program on streamers' viewer retention and acquisition.

Implications

With the facilitation of streaming and social technologies, streaming platforms have experienced exponential development in recent years. For instance, Facebook, one of the leading social media platforms, saw the live streaming channel growing more than four times in 2021 (Wise, 2022). Yet, many streaming platforms are facing nontrivial challenge in retaining and attracting individual streamers with content contribution, which is critical for the sustainable growth of the platform. The popular streaming platform Twitch suffered a 9.6% decrease of streaming channels in Q2 2021, and the total streaming channels dropped from 11.4 million to 10.4 million (May, 2021).

Although previous studies have examined the adverse effects of monetary incentives on voluntary behavior, little is known about how to mitigate the negative effects of monetary incentives on UGC, especially UGC in live streaming. Our empirical efforts highlight how a novel design of goal attainment incentive based on viewer gifting support can be a viable option for live streaming platforms to motivate streaming effort commitment from individual streamers. Compared to a simple financial award that might crowd out intrinsic motivation of streamers, goal attainment incentives could stimulate streamers' efforts on streaming production with higher viewer engagement because it combines the monetary incentives with viewer gifting support. Our overarching findings confirm that the incentive scheme not only drives streamers' streaming efforts but also motivate streamers to product more engaging streaming content. These findings improve the related theory of incentives on UGC. Goal incentives can not only effectively prevent the adverse impact of monetary incentives on the streamers but also reduce the negative impact on the audience. These findings are nontrivial for streaming platforms that face the challenge of streaming supply as we point out the effectiveness of the performance-based incentive program in driving streamers' efforts commitment. In addition, our exploration of the moderating role of prior goal completion also suggests that a hierarchical design of the incentive program could further drive streamers' motivation, which should be considered by platform managers when designing the incentive scheme.

Limitations

This work bears a number of limitations that serve as opportunities for future research. First, our empirical setting only allows us to focus on the relatively short-term (6-week period) impact of the incentive program on streamers' streaming motivation. Future study might investigate how such incentive could drive the long-term streaming commitment of individual streamers. Second, due to the company's data protection policy, we are unable to access the streaming content and communication comment in our analyses. Thus, our measurements on viewer engagement are only limited to understanding the viewing length and number of comments. It would be very useful to conduct video-mining in order to provide in-depth insights about how the incentive program alters streamers' streaming content and interaction with viewers. For example, future research might investigate how the goal attainment incentive could drive the facial expression and sentiment of the streamer, and how streaming content flow is different if streamers want to attract more gifting behaviors from viewers. Third, the number of tiers and the incentive of each tier have been predetermined by the company and it is worthwhile to design a experiment to test the effect of the incentive with different tiers and amount so that platform managers can harness the optimal return of the investment.

Reference

Ariely, D., Bracha, A., & Meier, S. (2009). Doing good or doing well? Image motivation and monetary incentives in behaving prosocially. *American economic review*, *99*(1), 544-555.

Bründl, S., & Hess, T. (2016). Why do users broadcast? Examining individual motives and social capital on social live streaming platforms.

Burtch, G., He, Q., Hong, Y., & Lee, D. (2022). How do peer awards motivate creative content? Experimental evidence from Reddit. *Management Science*, *68*(5), 3488-3506.

Burtch, G., Hong, Y., Bapna, R., & Griskevicius, V. (2018). Stimulating online reviews by combining financial incentives and social norms. *Management Science*, *64*(5), 2065-2082.

Cabral, L., & Li, L. (2015). A dollar for your thoughts: Feedback-conditional rebates on eBay. *Management Science*, *61*(9), 2052-2063.

Chen, H., Hu, Y. J., & Huang, S. (2019). Monetary incentive and stock opinions on social media. *Journal of Management Information Systems*, *36*(2), 391-417.

Deci, E. L., Koestner, R., & Ryan, R. M. (1999). A meta-analytic review of experiments examining the effects of extrinsic rewards on intrinsic motivation. *Psychological bulletin*, *125*(6), 627.

Fietkiewicz, K. J., Dorsch, I., Scheibe, K., Zimmer, F., & Stock, W. G. (2018). Dreaming of stardom and money: Micro-celebrities and influencers on live streaming services. In *Social Computing and Social Media. User Experience and Behavior: 10th International Conference, SCSM 2018, Held as Part of HCI International 2018, Las Vegas, NV, USA, July 15-20, 2018, Proceedings, Part I 10* (pp. 240-253). Springer International Publishing.

Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information systems research*, *19*(3), 291-313.

Frey, B. S. (1994). How intrinsic motivation is crowded out and in. *Rationality and society*, *6*(3), 334-352.

Frey, B. S., & Gallus, J. (2017). Volunteer organizations: Motivating with awards. *Economic psychology*, 273-286.

Friedlander, M. B. (2017). Streamer motives and user-generated content on social live-streaming services. *Journal of Information Science Theory and Practice*, *5*(1), 65-84.

Gallus, J. (2017). Fostering public good contributions with symbolic awards: A large-scale natural field experiment at Wikipedia. *Management Science*, *63*(12), 3999-4015.

Ge, R., Zheng, Z., Tian, X., & Liao, L. (2021). Human–robot interaction: When investors adjust the usage of robo-advisors in peer-to-peer lending. *Information Systems Research*, *32*(3), 774-785.

Gneezy, U., & Rustichini, A. (2000). Pay enough or don't pay at all. *The Quarterly journal of economics*, *115*(3), 791-810.

Gneezy, U., Meier, S., & Rey-Biel, P. (2011). When and why incentives (don't) work to modify behavior. *Journal of economic perspectives*, *25*(4), 191-210.

Goes, P. B., Guo, C., & Lin, M. (2016). Do incentive hierarchies induce user effort? Evidence from an online knowledge exchange. *Information Systems Research*, *27*(3), 497-516.

Gros, D., Wanner, B., Hackenholt, A., Zawadzki, P., & Knautz, K. (2017). World of streaming. Motivation and gratification on Twitch. In *Social Computing and Social Media. Human Behavior: 9th International Conference, SCSM 2017, Held as Part of HCI International 2017, Vancouver, BC, Canada, July 9-14, 2017, Proceedings, Part I 9* (pp. 44-57). Springer International Publishing.

He, C., Ozturk, O. C., Gu, C., & Silva-Risso, J. M. (2021). The end of the express road for hybrid vehicles: Can governments' green product incentives backfire?. *Marketing Science*, *40*(1), 80-100.

Heyman, J., & Ariely, D. (2004). Effort for payment: A tale of two markets. *Psychological science*, *15*(11), 787-793.

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.

Hu, M., Zhang, M., & Wang, Y. (2017). Why do audiences choose to keep watching on live video streaming platforms? An explanation of dual identification framework. *Computers in human behavior*, *75*, 594-606.

Huang, N., Burtch, G., Gu, B., Hong, Y., Liang, C., Wang, K., ... & Yang, B. (2019). Motivating user-generated content with performance feedback: Evidence from randomized field experiments. *Management Science*, *65*(1), 327-345.

Huang, N., Hong, Y., & Burtch, G. (2017). Social Network Integration and User Content Generation. *MIS quarterly*, *41*(4), 1035-1058.

Hukal, P., Henfridsson, O., Shaikh, M., & Parker, G. (2020). Platform Signaling for Generating Platform Content. *Mis Quarterly*, *44*(3).
Kosfeld, M., & Neckermann, S. (2011). Getting more work for nothing? Symbolic awards and worker performance. *American Economic Journal: Microeconomics*, *3*(3), 86-99.
Li, X., & Hitt, L. M. (2008). Self-selection and information role of online product reviews. *Information Systems Research*, *19*(4), 456-474.
Lin, Y., Yao, D., & Chen, X. (2021). Happiness begets money: Emotion and engagement in live streaming. *Journal of Marketing Research*, *58*(3), 417-438.
Liu, Y., & Feng, J. (2021). Does money talk? The impact of monetary incentives on user-generated content contributions. *Information Systems Research*, *32*(2), 394-409.
Lu, S., Yao, D., Chen, X., & Grewal, R. (2021). Do larger audiences generate greater revenues under pay what you want? Evidence from a live streaming platform. *Marketing Science*, *40*(5), 964-984.
Lu, Z., Xia, H., Heo, S., & Wigdor, D. (2018, April). 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).
May, E. (2021). "Streamlabs and Stream Hatchet Q3 2021 Live Streaming Industry Report ," . URL https://blog.streamlabs.com/streamlabs-and-stream-hatchet-q3-2021-live-streaming-indu
Mudambi, S. M., & Schuff, D. (2010). Research note: What makes a helpful online review? A study of customer reviews on Amazon. com. MIS quarterly, 185-200.
Pu, J., Chen, Y., Qiu, L., & Cheng, H. K. (2020). Does identity disclosure help or hurt user content generation? Social presence, inhibition, and displacement effects. Information Systems Research, 31(2), 297-322.
Qiao, D., Lee, S.-Y., Whinston, A. B., & Wei, Q. (2021). Mitigating the Adverse Effect of Monetary Incentives on Voluntary Contributions Online. Journal of Management Information Systems, 38(1), 82–107.
Qiu, L., & Kumar, S. (2017). Understanding voluntary knowledge provision and content contribution through a social-media-based prediction market: A field experiment. Information Systems Research, 28(3), 529-546.
Scheibe, K., Fietkiewicz, K. J., & Stock, W. G. (2016). Information behavior on social live streaming services. Journal of Information Science Theory and Practice, 4(2), 6-20.
Southern, M. (2021). "YouTube Paying Creators For Best Shorts Videos Every Month," . URL https://www.searchenginejournal.com/youtube-paying-creators-for-best-shorts-videos-every-month/406703/#close
Statista (2022). "Live streaming - statistics facts," . URL https://www.statista.com/topics/8906/live-streaming/#topicHeader__wrapper
Sun, M., & Zhu, F. (2013). Ad revenue and content commercialization: Evidence from blogs. *Management Science*, *59*(10), 2314-2331.
Sun, Y., Dong, X., & McIntyre, S. (2017). Motivation of user-generated content: Social connectedness moderates the effects of monetary rewards. *Marketing Science*, *36*(3), 329-337.
Susarla, A., Oh, J. H., & Tan, Y. (2012). Social networks and the diffusion of user-generated content: Evidence from YouTube. *Information systems research*, *23*(1), 23-41.
Törhönen, M., Sjöblom, M., Hassan, L., & Hamari, J. (2020). Fame and fortune, or just fun? A study on why people create content on video platforms. *Internet Research*, *30*(1), 165-190.
Vana, P., & Lambrecht, A. (2021). The effect of individual online reviews on purchase likelihood. *Marketing Science*, *40*(4), 708-730.
Wang, J., Li, G., & Hui, K. L. (2022). Monetary incentives and knowledge spillover: Evidence from a natural experiment. *Management Science*, *68*(5), 3549-3572.
Wasko, M. M., & Faraj, S. (2005). Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS quarterly*, 35-57.
Wise, J. (2022). "Live Streaming Statistics 2022: Industry Size Demographics ," . URL https://earthweb.com/streaming-statistics/
Wu, C., Che, H., Chan, T. Y., & Lu, X. (2015). The economic value of online reviews. *Marketing Science*, *34*(5), 739-754.
Yuen, M. (2022). "The future of livestreaming: trends and key stats for 2022," . URL https://www.insiderintelligence.com/insights/livestreaming-trends-stats/
Zhang, S., Lee, D., Singh, P. V., & Srinivasan, K. (2022). What makes a good image? Airbnb demand analytics leveraging interpretable image features. *Management Science*, *68*(8), 5644-5666.

Zhang, X., & Zhu, F. (2011). Group size and incentives to contribute: A natural experiment at Chinese Wikipedia. *American Economic Review*, *101*(4), 1601-1615.
Zhao, K., Lu, Y., Hu, Y., & Hong, Y. (2022). Direct and Indirect Spillovers from Content Providers' Switching: Evidence from Online Livestreaming. *Information Systems Research*.
Zhao, Q., Chen, C. D., Cheng, H. W., & Wang, J. L. (2018). Determinants of live streamers' continuance broadcasting intentions on Twitch: A self-determination theory perspective. *Telematics and Informatics*, *35*(2), 406-420.