# Analysis of pay-what-you-want donation behavior in game communities on social live streaming services

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## ABSTRACT
It is becoming more and more common in online services for service recipients to make donations when they are satisfied with the service provided by the service provider. Since these donations have no upper limit and can be repeated, they can be thought of as Pay-What-You-Want (PWYW) donations. This study takes Twitch as a case study and statistically analyzes the PWYW donation behaviors in live streaming channels on Twitch, where a community consists of a service provider (a live streamer) and the service recipients (viewers). The study reveals that viewer PWYW donation behaviors are influenced by the degree of viewer congestion in a channel by analyzing the top 100 live streaming channels on Twitch. Moreover, the study also reveals the large degree of channel diversity among the top 100 channels.

## Keywords
Pay-What-You-Want, PWYW donation, social live streaming services, subscription gifting

## INTRODUCTION
In the spring of 2020, the COVID-19 pandemic forced people to limit their outings, work from home, and study at home. It has also dramatically expanded the business of online games and other social live streaming services such as Twitch (Sanchez-Kumar, 2020).

In social live streaming services, a variety of live streaming channels are available to the public, and a wide variety of interactions are observed between live streamers and viewers. When a viewer is satisfied with the streamer's live broadcasting, the viewer can donate to the streamer. A viewer doesn't need to donate, but they tend to do so to show gratitude for the streamer's performance and cheer the streamer on for future performances. There is no limit to the amounts of money that can be donated to a streamer (in some services, there may be an upper limit). Therefore, donations to these services can be considered as Pay-What-You-Want (PWYW) donations, where viewers can freely decide the payment amount. The PWYW donations paid will be divided

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between the streamer and the social live-streaming service platform at a specific ratio. PWYW donations have also started and been increasing in online services such as Twitter (Nguyen, 2021). These donations have been expanding dramatically during the COVID-19 pandemic and are expected to be a new means of monetization in the post-COVID-19 era for online services (Kunigita et al. 2021). Therefore, understanding the motivation of viewers making PWYW donations would be significant in terms of “Bringing Worlds Together” based on digital games in the post-COVID-19 era.

There have been many studies on viewer engagement for favorite streamers including PWYW donations. Previous studies have analyzed engagement, for example, by focusing on the size of the live game community (Hilvert-Bruce et al. 2018) or by using the size of the number of followers of a streamer as an indicator of engagement (Gros et al. 2018). However, the size of the game community and the number of followers are constant numbers that do not change over time. In PWYW donation behavior, the interaction between streamers and viewers in live streaming channels may influence the donation behavior in real-time. Therefore, it is necessary to search for time-varying indicators that influence this behavior in live streaming channels. This study analyzes the influence of social density, which indicates the degree of viewer congestion in a particular streamer channel.

In this study, we use Twitch as a case of social live streaming services. Using public data from Twitch, we will investigate the following two hypotheses statistically. The public data include the number of concurrent viewer accesses and the number of followers in certain periods. We reveal that the social density of viewers, i.e., an indicator of viewer congestion, over the top 100 live streaming channels is one of the major factors in PWYW donation behavior.

Hypothesis 1: PWYW donation behavior from viewers to a streamer in a live streaming channel is affected by the number of concurrent viewer accesses, which is related to social density.

Hypothesis 2: PWYW donation behavior from viewers to a streamer in a live streaming channel is not affected by increases and decreases in the number of followers, which is not related to social density.

This study can contribute to the digital game industry in the post-COVID-19 era by demonstrating the effectiveness of PWYW as a new means of monetization.

## THEORETICAL BACKGROUND

### PWYW Donation

Pay-What-You-Want (PWYW) is a pricing mechanism in which goods/service prices are determined by the buyers. In this business model, buyers evaluate the value of goods/services offered by sellers and decide the prices based on their judgment. If buyers are satisfied with the quality of the goods/services, they then decide to purchase them at a higher price. As a result, sellers can maximize their profit, and they will make more effort to refine the quality of goods/services.

In the early stages, PWYW was introduced in real-world settings such as restaurants, and since then, it has become increasingly used in online services. Twitch is one of such examples that has introduced donation mechanisms and uses what is essentially considered a PWYW scheme. While Twitch does not seem to be involved in PWYW at first glance, it essentially is because there is no upper limit to the number of donations. The service recipients (viewers) can determine the final total amount of monetary rewards that they give to the service/content provider (the favorite streamer). In previous research (e.g., Wan et al. 2017), this kind of donation in online services is called a PWYW donation.

Since 2010, numerous studies have been conducted on PWYW in real-world settings, such as those involving a lunch buffet, cinema tickets, café drinks, and souvenir photos. Kim et al. (2009) and Gneezy et al. (2010, 2012) analyzed the determinants of PWYW behavior in real-world settings such as paying at restaurants and purchasing souvenir photos. However, research on online PWYW donations is very limited.

Wan et al. (2017) studied YY.com, a video-based social network in China, and found that viewers' attachment to content creators encourages donation, and one of the factors that boost this attachment is real-time interaction between buyers and sellers. However, their study was based on a questionnaire survey of viewers and did not analyze the relationship between donation behavior and data obtained from the service, such as the number of concurrent viewer accesses. In this study, we use the data available from the Twitch social live streaming service and analyze the PWYW donation behavior of viewers in live streaming channels.

## Overview of Twitch Social Live Streaming Service

### *Donation Services on Twitch*

Twitch is an innovative live streaming service, and in particular, Twitch's low latency video technology is the key to the stress-free broadcasts from streamers to the viewers. And the smooth interactions between streamers and viewers enable viewers to donate in response to the streamer`s excellent gameplay. The donations covered in this study are the common fun ways for the viewers to voluntarily support their favorite streamer, and different from simple charities for social contribution, such as Game Done Quick (GDQ) (gamesdonequick.com, 2021).

On Twitch, users can create a basic account for free, though free users are subjected to advertisements and cannot access various benefits that are exclusive to paid accounts. If viewers want to watch a particular streamer's gameplay, they need to pay for a subscription or need to be gifted a subscription of the streamer's gameplay. The subscription has three tiers: Tier 1 at $4.99/month, Tier 2 at $9.99/month, and Tier 3 at $24.99/month.

We consider the donation in Twitch is a PWYW donation, since viewers can use the donation services provided by Twitch to donate arbitrarily and repeatedly without any monetary limit. Twitch PWYW donation is a combination of two mechanisms, Bits and subscription gifting. Bits are virtual currency in Twitch. Viewers can purchase a minimum of 100 Bits for $1.40, and they can donate to a streamer during his or her gameplay as much and as often as they want. Viewers can also gift a subscription of a favorite streamer to other viewers repeatedly, so that their favorite streamer can get Bits during the gameplay and the subscription fee. In this study, we use this subscription gifting as a case study of PWYW donation.

The Twitch user interface (UI) is designed in a way to accelerate the recursive relationship between streamers and viewers. The viewers donate Bits and gift subscription in the chat window. In return, the viewers receive a Gifter Badge that is usually placed next to their online name in the chat window, so that the streamer and other viewers can recognize the donations.

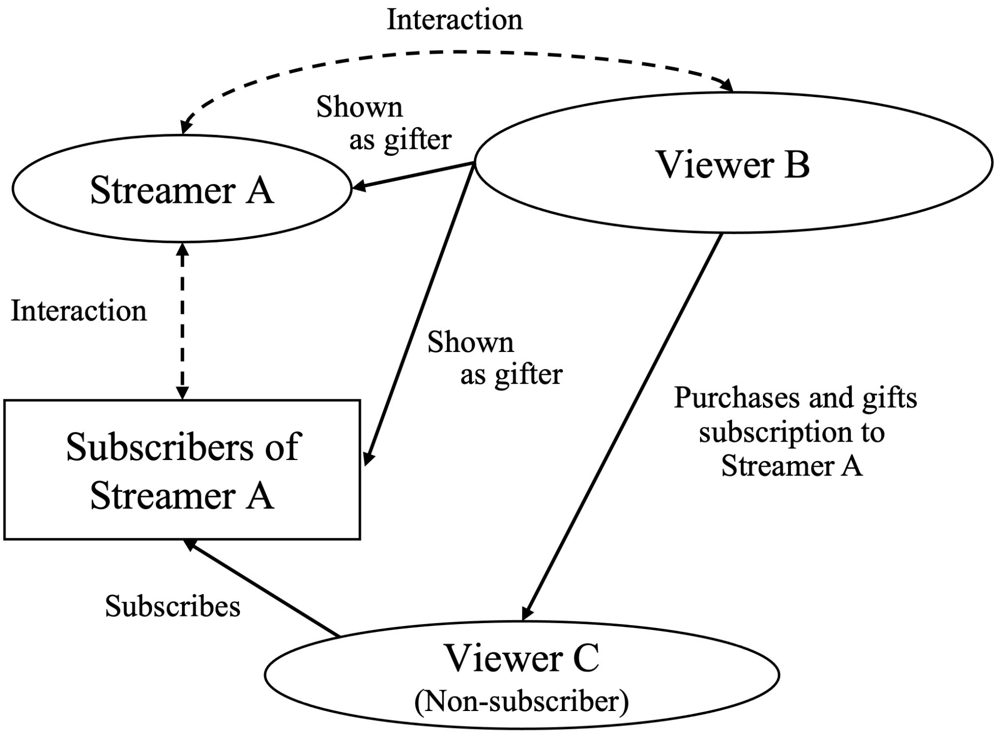


**Fig. 1: Flow of subscription gifting.**

Figure 1 illustrates a subscription gifting. Specifically, a viewer (Viewer B) can gift a subscription for a specified streamer (Streamer A) to an unsubscribed viewer (Viewer C). Viewer B first purchases a subscription to Streamer A by selecting one of the three tiers. Next, Viewer B gifts the subscription to Viewer C who is not subscribed to Streamer A yet. Viewer C receives the gift and joins Streamer A's channel as a subscriber. A Gifter Badge is displayed next to Viewer B's online name in the channel's chat window when the gifting is complete, so Viewer B's contribution is visible to Streamer A and other viewers. The streamer can see from whom a subscription was gifted and express his or her gratitude in the chat window and/or vocally. The viewer who gifted the subscription feels acknowledged and satisfied with the relationship he or she has established with the streamer. Later, the subscription gifting fees can be divided between Twitch and the streamer at a specific ratio.

## Social Density

### *Previous Research on Social Density*

Research related to social density such as Goffman's sociological research has been conducted since the 1970s (Goffman 1971 and 1974), and experiments have been conducted since around 2010. Levav and Zhu (2009) performed various experiments involving people in the real world and revealed that people tend to make certain choices when they are put in a high social density situation. For example, when people are crowded together, that is, social density is high, and they tend to choose a greater variety of snacks and minor brands. Also, when a supermarket is crowded, customers tend to choose products in a wider variety of categories. As a result, supermarkets sell a greater variety of products during busy hours.

Xu et al. (2012) expanded the study to investigate dynamic changes in social density, e.g., when a sudden movement of people causes social density to change drastically. They found that when social density is low, customers are likely to choose a mainstream product, but when there is a sudden increase in people, they tend to choose a more unique product.

The above behaviors indicate that people feel their individuality is threatened when social density increases, so they tend to assert themselves by choosing the option that differs from those of others. In the case of viewers' behavior in social live streaming services, for example, when social density is high, viewers are likely to take a variety of actions, including donating, to stand out to the streamer.

O'Guinn et al. (2015) revealed that social density affects people's income forecasts and price evaluations of products such as shoes. For example, when social density is high, the price evaluation of a product is low, and the likelihood of people spending money increases. Additionally, Maeng and Tanner (2013) clarified that people are more likely to construe objects more simply and concretely when social density is high.

From the above two studies, it can be concluded that a higher social density lowers the decision threshold. In the case of the donation behavior of viewers in social live streaming services, for example, when social density is high, the price evaluation of a donation is thought to be low, and the motivation to donate increases.

### *Virtual Crowdedness Based on Social Density*

How can livestream viewers perceive changes in social density in the virtual world? Twitch users can observe and experience the following:

- Speed of live chat: As the number of concurrent viewers increases, the flow of written messages appearing and scrolling out of view increases, making it difficult to visually confirm if a message was successfully posted without scrolling back up the chat window.
- Lack of individual presence: When viewers' posts are swept away and cannot be seen, it becomes impossible to assert one's presence on the channel. Viewers feel as if their presence is constantly being threatened.
- Acknowledgement: Viewers can go unnoticed by the streamers they like. Viewers aim to stand out from the rest of the fans, but when the posts move quickly and disappear from the chat as described above, they cannot stand out.

This study uses data on streamers' monthly average concurrent viewers taken from TwitchTracker.com as an indicator of the social density on streamers' channels.

## Previous Research on Social Live Streaming Services

Several studies related to social live streaming services have been conducted in recent years, such as on the interaction between streamers and viewers (Karhulahti 2016; Wohn et al. 2019; Rechenwald 2018; Lin et al. 2019) and gender-related issues (Routsalainen and Friman 2018; Siutila and Havaste 2018) on the services. However, studies considering the number of concurrent viewers on each streamer's channel or their comments in chat windows are very limited.

Hilvert-Bruce et al. (2018) analyzed the relationship between engagement with a streamer and the community size given a collection of the streamer's viewers as a community. First, regardless of the community size, engagement is motivated by social interaction and a sense of community. However, the smaller the community size, the more it is motivated by social engagement (e.g., emotional connection). In other words, viewers in a smaller community have a greater level of engagement with the streamer. Their study only statically verified community size. In this study, the number of viewers and followers in a live streaming channel, as well as the number of PWYW donations, changes over time.

Gros et al. (2018) analyzed the interaction and usage behavior of Twitch users based on the size of the number of followers of a streamer, but the number of followers was treated as a constant. In this study, the increase and decrease in the number of followers over time are used.

Li et al. (2019) interpreted the number of comments per minute posted in the chat window on a streamer's channel as an indicator of social density when analyzing a social live streaming service in China. However, their study focused on analyzing the relationship between the viewers' classes such as membership level and motivation toward digital gifting to a streamer and other viewers. The concept of social density was used as one parameter to analyze this relationship but only in the context of explaining this relationship. Our study analyzes the number of viewers and followers and their donation behavior as it changes over time.

## METHOD

### Data Collection

Twitch streamers who are entitled to receive donations are called Partners. In 2020, there were more than 50,000 Partners associated with Twitch (TwitchTracker.com, 2021). Partners are ranked in order of the number of subscribers, and the ranking is updated daily on TwitchTracker.com. In this study, we analyzed the top 350 Partners. We excluded those outsides of the top 350 because they have fewer than 100 gifted subscriptions per month. The time frame for selecting the top 350 was set to 19 months, from October 2019 to April 2021, because a large number of new streamers signed up after May 2021 due to the COVID-19 pandemic and the rankings changed drastically afterward. Among the top 350 streamers, 100 of them remained Partners of Twitch for the entire 19 months. Thus, these 100 streamers were selected for the analysis.

The breakdown of the 100 streamers is as follows:

English-language streamers: 77, Non-English-language streamers: 23

Males: 90, Females: 7, Unknown: 3 (a virtual streamer and team streamers)

We extracted the following four types of variable data for these 100 streamers from TwitchTracker.com for 19 months between October 2019 and April 2021. Since we extracted data for 19 months for each streamer, we had 100 (streamers) × 19 (months) = 1,900 pieces of data for each variable.

- $V_{ij}$: Monthly gifted subscription count by streamer
- $W_{ij}$: Monthly hours streamed by streamer
- $X_{ij}$: Average monthly concurrent viewers by streamer
- $Z_{ij}$: Increase and decrease in the number of followers per month by streamer

  *'i': Streamer number from 1 to 100.

  *'j': Index denoting data for 19 months in October 2019 and April 2021, from 1 to 19.

"Monthly gifted subscription count by a streamer (V)" is the number of gifted subscriptions that the streamer has received in a month. In this study, we consider it as the number of PWYW donations received in a month. Since subscription gifting is usually done at Tier 1, $4.99/month, the analysis is based on the number of donations, not the amount of donations. "Monthly hours streamed by a streamer (W)" is the number of hours that a streamer broadcasts in a month. Also, "Average monthly concurrent viewers (X)" is the average number of concurrent viewers accessing the streamer channel per hour in a month. A viewer can see the number of simultaneous accesses displayed on the screen when viewing the streamer channel. This makes the viewer aware of the presence of others, even in an online space. Finally, "Increase and decrease in the number of followers per month by a streamer (Z)" is the number of increases or decreases in the number of followers for the streamer in a month.

Additionally, we created a new variable, "Monthly gifted subscription count per hour (Y)," from variables V and W as follows.

- Monthly gifted subscription count per hour by a streamer ($Y_{ij}$) = $V_{ij}/W_{ij}$

As explained in the subsection below, we use this "Monthly gifted subscription count per hour by a streamer (Y)" as an objective variable in the multiple regression analysis models.

The mean, standard deviation, minimum and maximum values for each of the 1,900 variables Y, X, and Z are shown in Table 1. The difference between the minimum and maximum values is large, and the standard deviation value is also larger than the average value. This is because the characteristics of the community formed by the streamer and viewers for each streamer differ greatly channel by channel. For example, when variable X or Z is about 10,000, the range of values for variable Y can vary from first place after the decimal point to a three-digit number by a factor of about 1,000. Therefore, it is necessary to conduct an analysis that takes into account the differences in the characteristics of communities.

| Variables | Mean value | Standard deviation | Minimum value | Maximum value |
|---|---|---|---|---|
| Monthly gifted subscription count per hour by each streamer (Y) | 17.6 | 22.0 | 0.2 | 243.0 |
| Average monthly concurrent viewers by each streamer (X) | 10,075.6 | 12,577.4 | 167.0 | 101,591.0 |
| Increase and decrease in number of followers per month by each streamer (Z) | 41,498.8 | 225,923.6 | -4,781,610.0 | 4,687,152.0 |

**Table 1: Variables statistics.**

## Dummy Variable for Each Community

Each streamer has a large number of viewers who form a kind of community. Thus, an analysis of these 100 streamers can be considered as an analysis of 100 communities. We assumed that each of the 100 communities has its own characteristics and can be classified into 100 categories. Therefore, we set a dummy variable $D_i$ (i = 1 - 99) to indicate the category of the community. As mentioned earlier, "i" indicates the number of the streamer. In addition, we denote the $n^{th}$ streamer as a streamer (n). The community of streamers (100) was used as a reference, and the communities from streamer (1) to streamer (99) were considered as different categories. Therefore, $D_i$=1 when i=n and $D_i$=0 when $i \neq n$ for the corresponding streamer (n), where n = 1 - 99, and all $D_i$=0 (i = 1 - 99), where n=100.

## Multiple Regression Model for Analysis

We used multiple regression analysis to test the two hypotheses of this study.

First, model 1 as shown in equation (1) was used to test hypothesis 1. The objective variable Y indicates the number of monthly PWYW donations per unit time. The explanatory variable X indicates the monthly average number of concurrent viewer accesses for each streamer channel. The explanatory variable X is an indicator of social density. In addition, we set a dummy variable in the explanatory variables to indicate the category of the community by streamer and viewers for each streamer.

Model 1: $Y = aX + \sum_{i=1}^{99}(b_i D_i) + c$ (1)

Y: Monthly gifted subscription count per hour by each streamer

X: Average monthly concurrent viewers by each streamer

$D_i$: Dummy variable for streamer i, 1 or 0

a, $b_i$, c: Coefficient

i: Streamer number from 1 to 99

Note: Y and X are the data of the 100 streamers over 19 months from October 2019 to April 2021

Next, model 2 as shown in equation (2) was used to test hypothesis 2. The objective variable Y indicates the number of monthly PWYW donations per unit time. The explanatory variable Z indicates the increase and decrease in the number of followers of each streamer channel during the month. In addition, we set a dummy variable in the explanatory variables to indicate the category of the community by streamer and viewers for each streamer.

Model 2: $Y = dZ + \sum_{i=1}^{99}(e_i D_i) + f$ (2)

Y: Monthly gifted subscription count per hour by each streamer

Z: Increase and decrease in the number of followers per month by each streamer

$D_i$: Dummy variable for streamer i, 1 or 0

d, $e_i$, f: Coefficient

i: Streamer number from 1 to 99

Note: Y and Z are data of the 100 streamers over 19 months from October 2019 to April 2021

The analysis was conducted by EZR (Easy R) based on its technical report (Kanda, 2013).

## FINDINGS

A summary of the multiple regression analysis results is shown in Table 2. Both models were significant at $p < 0.001$ and Adjusted $R^2 > 0.50$. For $R^2$, studies on social media relevant to Twitch usually set the threshold above 0.50 (e.g., Li et al., 2020). Therefore, both multiple regression models in this study can mostly reveal the major factor of the objective variable. Also, the significance of the individual explanatory variables in each model is shown in Tables 3 and 4, which show only variables X and Z and dummy variables from 1 to 10 due to space constraints.

| Multiple regression analysis models | Adjusted $R^2$ | p-value | Significance |
|---|---|---|---|
| Equation (1) to test hypothesis 1 | 0.685 | 0.000 | Significant |
| Equation (2) to test hypothesis 2 | 0.662 | 0.000 | Significant |

**Table 2: Summary of Analysis Results.**

In model 1, which tested hypothesis 1, the explanatory variable X was significant as shown in Table 3. This shows that "Average monthly concurrent viewers by each streamer," an indicator of social density, is related to the objective variable, i.e., the number of PWYW donations per unit time. In addition, 54 out of 99 dummy variables (55%) were significant.

| Coefficient | Estimate | t-value | p-value | Significance |
|---|---|---|---|---|
| a | 0.001 | 11.361 | 0.000 | Significant*** |
| c | 2.032 | 0.715 | 0.475 | Not significant |
| $b_1$ | 22.358 | 5.393 | 0.000 | Significant*** |
| $b_2$ | 1.216 | 0.294 | 0.768 | Not significant |
| $b_3$ | -5.940 | -1.353 | 0.176 | Not significant |
| $b_4$ | 23.053 | 5.437 | 0.000 | Significant*** |
| $b_5$ | 12.286 | 2.954 | 0.003 | Significant** |
| $b_6$ | 5.118 | 1.271 | 0.204 | Not significant |
| $b_7$ | 44.609 | 10.699 | 0.000 | Significant*** |
| $b_8$ | -8.204 | -2.038 | 0.042 | Significant* |
| $b_9$ | 40.108 | 10.008 | 0.000 | Significant*** |
| $b_{10}$ | 57.686 | 14.386 | 0.000 | Significant*** |

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

**Table 3: Analysis Results for Model 1.**

Next, in model 2, which tested hypothesis 2, explanatory variable Z was not significant as shown in Table 4. This shows that "Increase and decrease in the number of followers per month by each streamer," i.e., increases or decreases in the number of followers, is not related to the objective variable, i.e., the number of PWYW donations per unit time. In addition, 52 out of 99 dummy variables (53%) were significant.

| Coefficient | Estimate | t-value | p-value | Significance |
|---|---|---|---|---|
| d | -0.000 | -0.048 | 0.962 | Not significant |
| f | 4.623 | 1.577 | 0.115 | Not significant |
| $e_1$ | 34.534 | 8.329 | 0.000 | Significant*** |
| $e_2$ | 12.621 | 3.043 | 0.002 | Significant** |
| $e_3$ | 14.538 | 3.500 | 0.000 | Significant*** |
| $e_4$ | 38.870 | 9.369 | 0.000 | Significant*** |
| $e_5$ | 25.059 | 6.041 | 0.000 | Significant*** |
| $e_6$ | 9.804 | 2.364 | 0.018 | Significant* |
| $e_7$ | 57.784 | 13.937 | 0.000 | Significant*** |
| $e_8$ | -3.527 | -0.850 | 0.395 | Not significant |
| $e_9$ | 38.415 | 9.265 | 0.000 | Significant*** |
| $e_{10}$ | 55.420 | 13.366 | 0.000 | Significant*** |

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

**Table 4: Analysis Results for Model 2.**

## DISCUSSION

### Social Density as One of the Major Factors

First, in this study, testing hypothesis 1 confirmed that the number of PWYW donations per unit time from viewers to a streamer is related to the number of concurrent viewer accesses in a game community for a streamer and viewers. In other words, the number of PWYW donations per unit time is higher when the number of concurrent viewer accesses is higher. Next, testing hypothesis 2 in this study confirmed that the number of PWYW donations per unit time from viewers to a streamer in a game community for a streamer and viewers is not related to increases and decreases in the number of followers.

Considering the difference between concurrent viewer accesses and an increase and decrease in the number of followers from the viewpoint of viewers, first, a viewer can recognize other viewers who are accessing a particular streamer's channel at the same time from the screen of the channel, from the time-varying number of concurrent accesses, from the number of the comments written to the chat, and from the speed of the flow of those comments in real time. However, the viewer cannot even recognize a sudden increase in the number of followers in real time. Also, even if the number of followers suddenly decreases, the viewer cannot recognize this in real time. Even if the number of people increases in the service, in the same way, the viewer can be aware of the degree of congestion in the streamer channel from the increase in the number of concurrent viewer accesses but not from the increase in the number of followers. This number of concurrent viewer accesses is an indicator of social density, which indicates the congestion of viewers in a particular streamer's channel. In other words, as the number of concurrent viewers accesses increases and social density becomes higher, social density characteristics, such as a sense of danger to one's own existence or evaluating the price for a donation as low, are activated, which is thought to promote PWYW donation behavior. Increases and decreases in the number of followers had nothing to do with the social density, which indicates the congestion of viewers in a particular streamer's channel. Therefore, from the two hypotheses tested in this study, it is clear that PWYW donation behavior from viewers in a live streaming channel is influenced by social density and is one of the major factors of PWYW donation behavior.

### Game Communities with Diversity

This study considered the diversity in the community formed for each streamer by the streamer and viewers. Therefore, we categorized 100 live streaming channels into 100 categories and set 99 dummy variables in the two models. The results of the analysis showed that both models were significant, with Adjusted $R^2 > 0.50$. In addition, more than 50% of the 99 dummy variables were significant in each of the two models. Even though the explanatory variable Z (increase and decrease in the number of followers) was not significant in model 2, model 2 by itself was significant, and more than 50% of the dummy variables were significant.

In this study, the number of PWYW donations per unit time was set as the objective variable, and specifically, the number of subscriptions gifted per unit time by viewers per community was used as the objective variable. This suggests that more than 50% of the 100 game communities had some diversity in subscription gifting as a community characteristic. Therefore, another dummy variable could be set up for further analysis, dividing between a group for which the dummy variable of the community category was significant this time and a group for which it was not significant this time. It would also be conceivable to set another objective variable for the group for which the dummy variable was not significant and analyze it. By doing these things, we will be able to get new findings.

## CONCLUSION

In this study, we took the Twitch social live streaming service as a case study and conducted a statistical analysis of PWYW donation behavior, which is spreading in online services that have expanded dramatically due to the COVID-19 pandemic. As a result, we revealed that social density, which indicates the degree of viewer congestion in live streamer channels, is one of the major factors in PWYW donation behavior in social live streaming services. This can contribute to the design of PWYW donation services in the online services expected to expand in the post-COVID-19 era.

Also, game communities formed by streamers and viewers were considered to have their own characteristics. It can be said that the game community in social live streaming services is characterized by real-time interaction between many viewers and their favorite streamers, and it will be meaningful to classify each game community as having different characteristics from other game communities.

Based on the results of this study, the authors will continue to analyze the major factors of PWYW donation behavior. By doing so, the authors can contribute to the game and social live streaming service industries and the "Bringing Worlds Together" movement based on digital games.

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