Typological analysis of pay-what-you-want donation behavior in virtual world

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ABSTRACT

The COVID-19 pandemic has significantly increased support activities by viewers who donate to artists and others through social tipping and digital gifts within virtual communities. These donations, provided by service recipients (buyers) to support service providers (sellers), are gifts and can be considered PWYW (pay-what-you-want) donations because there is no upper limit to the number of donations. This study focused on Twitch, a live-streaming platform, and conducted a cluster analysis of the log data from the top 100 streamers' virtual communities. We classified these 100 communities, comprising streamers and viewers, into four groups based on characteristics of PWYW donation behavior. Using service-dominant logic as our analytical framework, we identified the distinct characteristics of each group. We also provide the theoretical and practical implications of the study results, contributing insights for future monetization strategies in support activities as society moves toward the digital twin and metaverse.

Keywords

pay-what-you-want (PWYW), PWYW donation, social live streaming services, social density, uses and gratifications theory, service-dominant (S-D) logic

INTRODUCTION

While the COVID-19 pandemic limited people's activities in the real world, it significantly expanded their engagements in the virtual world (Sanchez-Kumar 2020). Virtual world activities are characterized by a large number of participants and diverse forms of interaction. For instance, over 12 million fans simultaneously accessed and participated in a virtual concert featuring rap artist Travis Scott as an avatar during the global lockdown due to the pandemic (Stuart 2020). Similarly, Justin Bieber's virtual concert, "An Interactive Virtual Experience," was highly interactive, enabling participants to chat with Justin and send him messages (Mumford 2022).

Proceedings of DiGRA 2025

In the virtual world, viewers who are fans often provide financial support to artists or other individuals through social tipping or digital gifts. This activity can be considered a pay-what-you-want (PWYW) donation because it is repeatable and has no monetary limits. A PWYW donation involves a service recipient (buyer) giving money to the service provider (seller) not as an act of charity, but as a support activity. Since the pandemic, PWYW donations have been introduced or expanded across various online services such as Twitter (now known as X), Facebook, and YouTube (e.g., (Crawford 2021) (Hutchinson 2021) (Silberling 2021)).

The level of activity in the virtual world has remained steady since the COVID-19 pandemic, with approximately the same number of participants as during the pandemic (e.g., (TwitchTracker.com 2021)). Since then, PWYW donations, as a support activity in the virtual world, have become well-established in various online services (Anwar 2022). PWYW donations are expected to further expand toward the digital twin and metaverse eras (e.g., (Tech Spotlight Blog 2023)). Therefore, it is reasonable to analyze PWYW donation behavior as a form of monetization support activities in the virtual world.

PWYW donations have been a feature of social live-streaming services, such as Twitch since before the pandemic (Fontaine 2016). However, prior studies have not considered whether there are differences in PWYW donation behavior between communities composed of service providers (streamers) and service recipients (viewers) (e.g., (Wan, et al. 2017) (Wohn, Freeman and McLaughlin 2018)). In social live-streaming services, each streamer forms a unique community. Therefore, depending on the streamer's personality and the traits of the viewers who are drawn to that community, the characteristics related to PWYW donation behavior are likely to vary from one community to another. If communities could be classified into groups based on the characteristics of viewers' PWYW donation behavior, it would aid in effectively monetizing support activities in the virtual world.

We used Twitch as a case study and conducted cluster analysis using k-means clustering with actual service data from the top 100 streamers across 100 communities to clarify the feasibility of classifying communities based on characteristics related to PWYW donation behavior. This analysis employed analytical framework and viewer-motivation theory, both of which consider a large number of participants and diverse interactions that characterize people's activities in the virtual world. To address the variety of interactions, service-dominant (S-D) logic, which assumes that service providers and recipients interact to co-create value in the service (Vargo and Lusch 2016), was used as the analytical framework. Additionally, the uses and gratifications theory (UGT) (e.g., (Katz, Gurevitch and Haas 1973) (West and Turner 2007)), was utilized as the motivational theory. The concept of social density (e.g. (Levav and Zhu 2009)), which suggests that the density of individuals in a particular space influences behavior, was used as a motivational theory for a large number of participants. This study contributes to the monetization of support activities in the virtual world for the digital twin and metaverse eras by deriving both theoretical and practical implications based on the analysis results.

THEORETICAL BACKGROUND

PWYW model

The PWYW is a pricing mechanism in which good/service prices are determined by a buyer's judgment. This approach was initially introduced in real-world settings such as restaurants, but since has gained significantly popularity online. Under this business model, buyers assess the value of goods and services provided by sellers and determine prices according to their judgment. If buyers are content with the quality, they may decide to pay a higher price. Accordingly, sellers can maximize their profits while continuously striving to improve the quality of their goods and services.

Twitch initiated donation mechanisms and applied what is essentially the PWYW scheme. Service recipients (viewers) can decide on the total amount of donations without a ceiling and donate repeatedly to the service provider (streamer). In a prior study (Wan, et al. 2017), this type of donation to online services was described as a PWYW donation.

Since 2010, many studies have been conducted on PWYW in real-world settings, such as buying buffet lunches, cinema tickets, café drinks, and souvenir photos (e.g., (Kim, Natter and Spann 2009) (Gneezy, Gneezy and Nelson, et al. 2010) (Gneezy, Gneezy and Riener, et al. 2012)). Studies have since extended the examination of online service areas such as digital music sales (e.g., (Kim, Kaufmann and Stegemann 2013) (Regner 2015)) and PWYW donation behavior in social live-streaming services (e.g., (Wan, et al. 2017) (Kunigita, Javed and Kohda 2023)).

Prior PWYW studies clarified that the relationship between the service provider (seller) and service recipient (buyer) is significant for receiving more rewards in the PWYW model. These studies also highlight that personal and real-time interactions and "reciprocity" should be key drivers. However, they did not consider whether PWYW donation behavior differs based on the community, consisting of service providers (streamers) and service recipients (viewers). We clarified that the characteristics related to PWYW donation behavior vary from one community to another.

Value Co-creation by Service Providers and Recipients

The S-D logic is a framework that regards both goods and services as "service," without distinguishing between them. It assumes that firms provide only value propositions, while customers define that value, and firms co-create value with their customers (Vargo and Lusch 2004). According to this logic, actors, comprising service providers and recipients, co-create value through resource integration and service exchange within nested and interlocking service ecosystems (Vargo and Lusch 2016). Logic defines operand resources (e.g., manufactured products) and operant resources (e.g., knowledge and skills) as resources. It also emphasized that "In particular, value co-creation is represented by the reciprocity of exchange." (Vargo and Lusch 2016)

S-D logic also states that value is co-created through interactions between the firm and customers. It notes that the interaction occur not only in person but also "in a virtual world" and can be described as "mutual or reciprocal action or influence." (Vargo and Lusch 2016) Thus, in both the virtual and real-world ecosystems, value co-creation occurs through interactions—specifically, reciprocal actions, operant resource integration, and service exchange among multiple actors. Value co-creation can, therefore, be expressed through the reciprocity of exchange.

Of the 11 Foundational Premises (FPs) of S-D Logic, FPs 6 and 10 were used in this study. The FP6 is defined as “Value is co-created by multiple actors, always including the beneficiary” (Vargo and Lusch 2016) and the FP10 is defined as “Value is always uniquely and phenomenologically determined by the beneficiary” (Vargo and Lusch 2008). The latter indicates that value is context-dependent and shaped by the circumstances of the beneficiary.

Previous studies on sports live streaming services and online gaming has shown strong relevance to social live streaming services, particularly through the S-D logic.

Hussain et al. (Hussain, et al. 2022) applied S-D logic to examine how value co-creation occurs between customers (gameplayers) and service providers (gaming firms) in premium gaming services through customer surveys. Their results revealed that interactions between customers and service providers result in customer satisfaction with new or improved features introduced to the services, as well as the associated costs. In other words, these interactions, in turn, improve the functionality and profitability of the services, facilitating value co-creation. Hussain et al. further emphasized that the co-creation framework enabling interactions between game players and gaming firms constitutes an integrated operant resource within the S-D logic framework.

Through viewer surveys, Qian used S-D logic to examine how viewers and co-streamers co-create value during Saturday night football (TNF) broadcasts co-streamed by prominent streamers (Qian 2022). The results revealed that the matching of co-streamers and TNF, as well as the interaction between viewers and co-streamers, significantly influenced continued TNF viewership. Additionally, these dynamics contributed to the co-creation of value in TNF's innovative sports live-streaming format. Qian states that the streamer's TNF “expertise” and the “relationships” that direct viewers to the service are key operant resources within the S-D logic.

These studies focused exclusively on the behavior of service recipients, overlooking the behavior of service providers (gaming firms and co-streamers), who represent the other actors in the S-D logic framework. Kunigita et al. performed a multiple regression analysis on the PWYW donation behavior of both streamers and viewers, using Twitch as a case study based on S-D logic. Their research demonstrated that the value co-creation of streamers' services occurs through an interactive framework that integrates the operant resources of both parties (Kunigita, Javed and Kohda 2023). The authors applied S-D logic as an analytical framework, using data on the PWYW donation behavior of both streamers and viewers to support their findings.

Social Density and Uses and Gratifications Theory

Research on social density, which indicates the density of people in a particular space, has been conducted through various experiments involving real-world people.

Levav and Zhu (Levav and Zhu 2009) found that people tend to make certain choices when placed in high social density. For instance, when people are crowded and social density is high, they tend to choose a greater variety of snacks and less popular brands. Xu et al. (Xu, Shen and Wyer Jr. 2012) extended their study to cases in which the social density changed significantly owing to the sudden movement of people. They found that customers are more likely to choose mainstream products when social density is low, but prefer more unique products when the number of people increases suddenly.

O'Guinn et al. (O'Guinn, Tanner and Maeng 2015) found that when social density is high, the price valuation of goods such as shoes decreases, people are more likely to spend money, and social density affects income projections. Maeng and Tanner (Maeng and Tanner 2013) also found that people were more likely to interpret objects in simple and concrete terms when their social density was high.

The above behaviors concerning choices indicate that people feel that their individuality is threatened when social density increases; therefore, they tend to assert themselves by choosing an option that differs from others. In addition, concerning the price evaluation and construction, it can be concluded that a higher social density lowers the decision threshold.

In social live streaming services such as Twitch, viewers can perceive changes or increases in social density in the virtual world based on the speed of the live chat. As the number of concurrent viewers increases, the display flow of posted messages becomes faster, making it challenging to determine whether messages have been properly posted without scrolling back through the chat window. When viewers' posts flow out of view and become invisible, they cannot effectively assert themselves on the channel and feel that their presence is being constantly undermined. In addition, viewers often tend to stand out to their favorite streamer over other viewers, but if the posts are quickly swept away and disappear from the chat window, as mentioned above, they may fail to stand out or be noticed by the streamer.

When the social density is high, viewers are likely to engage in a variety of behaviors, including PWYW donations for self-presentation. In this case, viewers' PWYW donation behavior is expected to lower their price evaluation of donations and increase their motivation to donate because of higher social density.

Prior studies on social live-streaming services, Li et al. (Li, et al. 2021) and Kunigita et al. (Kunigita, Javed and Kohda 2022) used the concept of social density to analyze PWYW donation behavior.

UGT analyzes the effects of media by examining how people use media in their lives and the types of gratification they derive from it. Analysis based on UGT often focus on needs gratified by the media, a framework originally created by Katz et al. (Katz, Gurevitch and Haas 1973) and later updated by West et al. (West and Turner 2007). These needs were classified into five types: cognitive, affective, personal integrative, social integrative, and tension release.

Sjöblom et al. surveyed Twitch users to analyze four types of usage and the abovementioned five needs as motivations based on the UGT (Sjöblom and Hamari 2017). The four usage types are: hours watched, streamers watched, streamers followed, and subscriptions. The analysis revealed that watching streaming was strongly associated with tension release, as well as social-integrative and affective motivations. The study also revealed that social integrative motivations are important for viewers to become streamer subscribers. Hilvert-Bruce et al. also conducted a survey of Twitch users based on UGT and analyzed viewer engagement in social live-streaming services (Hilvert-Bruce, et al. 2018). They established eight motivations for engagement, six of which were found to significantly contribute to viewer engagement. The six motivations identified are social interaction, sense of community, meeting new people, entertainment, information seeking, and lack of external support. The authors noted that the motivating factors for becoming a subscriber and donating are social interactions and a sense of community. While becoming a subscriber and donating are not necessarily the same, there is a relationship between them. Therefore, Sjöblom et al. and Hilvert-Bruce et al. share the finding that the desire to belong to a community is a key motivation for donating.

We used the concepts of social density and UGT as analytical methods, in addition to the S-D logic as the analysis framework.

Typological Analysis

Prior studies on social live-streaming services have conducted typological analyses of viewers' user engagement with streamers. Hilvert-Bruce et al. identified four types of user engagement based on a survey of Twitch viewers (Hilvert-Bruce, et al. 2018). Liu et al. collected data on viewers of the ITTF World Tour Grand Final 2019, who streamed live on China Sport, and conducted a clustering analysis to classify viewers into four groups based on S–D logic (Liu, Tan and Wu 2023).

However, prior studies have broadly categorized viewers' user engagement with streamers and have not typologized PWYW donation behavior between streamers and viewers. It has also not been considered that each community, composed of a streamer and viewers, has its own characteristics, which makes the viewer the unit of analysis, rather than the community. We classified communities, composed of streamers and viewers, based on characteristics related to PWYW donation behavior.

Donation Mechanism on Twitch Social Live-streaming Service

Twitch is a state-of-the-art live-streaming service that provides low-latency video technology, ensuring stress-free and highly interactivity between streamers and viewers. While viewers can create a free basic account, they must subscribe to a streamer's channel—either through a paid subscription or by receiving a gifted one—to avoid ads and access archived videos.

Twitch's PWYW donation system combines two mechanisms: Bits and subscription gifting. Bits represent virtual currency on Twitch, with viewers able to purchase a minimum of 100 Bits for $1.40 and donate to a streamer as much and as often as they like. Viewers can also repeatedly gift subscriptions to their favorite streamers to other viewers.

A viewer (Viewer B) can gift a subscription to a designated Streamer A (Streamer A) to an unsubscribed viewer (Viewer C), as shown in Figure 1. First, Viewer B purchases a subscription to Streamer A and gives it to Viewer C, who has not yet subscribed to the Streamer A channel (Figure1 (a)). After receiving the subscription, Viewer C can join Streamer A's channel as a subscriber (Figure1 (b)). Once the subscription gift is completed, a gifter badge appears in the chat window next to Viewer B's online name, visible to Streamer A and other viewers, including Viewer C. Viewer B feels acknowledged and satisfied with their connection to Streamer A.

Streamers can expect both an increased number of subscribers and more bits from the growing number of subscribers through subscription gifting. Streamers are also paying attention to the concept of "subathon," a term coined from "subscriber" and "marathon," whereby for each new subscriber, the streamer extends the streaming time by about 10 minutes, thereby increasing interaction time with viewers (Lorenz 2021). Thus, viewers can intentionally extend the streamer's streaming time using a "subathon" by giving a subscription. It is assumed that streamers expect subscription gifting, not one-off Bits, as PWYW donations. Thus, this study uses subscription giving as a case study of PWYW donations.

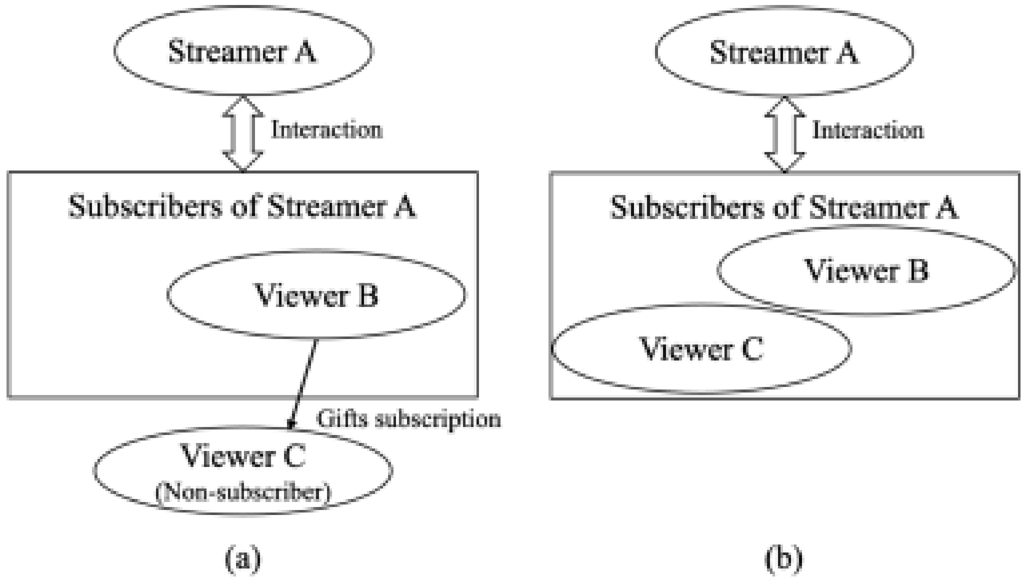

Figure 1: Flow of subscription gifting.

DATA FOR ANALYSIS AND HYPOTHESIS DEVELOPMENT

Statistics Websites for Social Live-streaming Services

This study used Twitch log data. The major websites that provide Twitch statistics are listed in Table 1. Only StreamsCharts.com (Streams Charts 2023) provides multi-service data, not just Twitch. Some of the statistics on these websites are displayed in a tabular format, whereas others are shown in a graphical format, with numerical data available when specific points are selected. These data are used for fan activities of particular streamers, various media articles, data-driven marketers, academic papers, and other purposes (e.g. (Starcraft on Reddit 2021) (BetMGM 2023) (Dean 2023) (Pollack, et al. 2021)).

Name of statistics site	Paid or free access	Services for which data are provided	Data display method
TwitchTracker.com	Free (subjected to advertisement)	Only Twitch	mainly numerically, by table
TwitchStats.com	Free (subjected to advertisement)	Only Twitch	Graphically, partially numerically
TwitchMetrics.net	Paid (limited free access)	Only Twitch	Numerically, graphically
StreamsCharts.com	Paid (limited free access)	Various ones such as Twitch, YouTube, AfreecaTV (Mainly, Korea) and BIGO LIVE (Mainly, Southeast Asia)	Numerically, graphically

Table 1: Major websites providing Twitch statistics.

The sites listed in Table 1 provide key log data on items common to each streamer, such as the average number of concurrent viewers, hours streamed, and PWYW donation. The authors used TwitchTracker.com, which is frequently cited in academic papers and offers free access to the numerical data in the tables (e.g., (Chae and Lee 2022) (Lamerichs 2021)).

Reciprocal Actions between Streamer and Viewers

The interaction between a streamer and viewers is not restricted to the streamer's live streaming of gameplay and the viewers' posting of assisting messages to the streamer in text in the chat window during the live stream. Hamilton et al. refer to Twitch as "live mixed media" because of the various ways it can be interacted with (Hamilton, Garretson and Kerne 2014).

Interactions that viewers can repeat to support streamers include text messages, icons called “emotes” on Twitch, and PWYW donation postings. However, these means of interaction are restricted to the chat window; therefore, as the concurrent viewer count increases and the chat window becomes crowded, it becomes difficult for viewers to visually confirm their own posts (Hamilton, Garretson and Kerne 2014). In other words, as the concurrent viewer count rises, chat window interactions become more competitive, requiring viewers to possess the knowledge and skills to perform these interactions effectively and consistently to support the streamer.

Streamers’ live streams include gameplay and live camera shots of the streamers' upper bodies. Therefore, since streamers are typically unable to post chats during gameplay, they interact with viewers through voice, facial expression changes, gestures, and other body movements to respond to text messages or “emotes” from viewers. Some streamers may also interact with the personalities and multifaceted nature of the streamers, such as dancing or introducing their favorite products when switching games. After gameplay ends, streamers often continue interacting via audio while viewers engage via chat posts. Therefore, the services provided by streamers involve more than just live gameplay streaming—they encompass a variety of interactions, which require streamers to have the necessary knowledge and skills to do so.

From the S-D logic perspective, the interactions between streamers and viewers can be considered reciprocal actions, performed using various means, requiring knowledge and skills as operant resources.

Variables for Analysis

Table 2 presents the definitions of the variables examined. The first variable was an indicator of PWYW donations. Wan et al. used virtual gift-giving in their study on YY.com (Wan, et al. 2017); therefore, we applied the number of gifted subscriptions per streamer as an indicator of PWYW donations.

The authors defined the second indicator as viewers' efforts and reciprocal actions. As the concurrent viewer count for a particular streamer's channel increases, the posts in the chat window become more crowded and competitive. Hamilton et al. describe this situation as "overly crowded chat rooms" (Hamilton, Garretson and Kerne 2014) and refer to it as "fast moving chat rooms" (Hilvert-Bruce, et al. 2018). Therefore, viewers struggle to use their knowledge and skills to support streamers and post texts, "emotes," and PWYW donations in the chat window within a restricted time. Thus, the number of concurrent viewers can be regarded as indicators of effort and reciprocal actions.

Authors define the third indicator as streamers' efforts and reciprocal actions. In addition to gameplay, streamers strive to interact with their viewers in a multifaceted manner, using their knowledge and skills. Woodcock and Johnson describe these behaviors as "affective labor" and "performance" by streamers to solicit donations from viewers (Woodcock and Johnson 2019). Therefore, the number of hours streamed inevitably increases (Woodcock and Johnson 2019). The "subathon" also increases the hours streamed by streamers, and streamers cannot receive PWYW donations unless they stream live. Thus, hours streamed can be regarded as an indicator of streamers' efforts and reciprocal actions.

Variables	Definition	References
Gifted-subscription count per streamer	Indicator of PWYW donation	Wan, et al., 2018
Concurrent viewers per streamer	Indicator of viewers' efforts and recipocal action by viewers	Hamilton, et al., 2014, Hilvert-Brice, et al., 2018
Hours streamed per streamer	Indicator of streamers' efforts and recipocal action by streamers	Woodcock & Johnson, 2019

Table 2: Definition of variables.

Hypothesis Development

In a community composed of service providers and recipients, from an S-D logic perspective, the two parties interact; that is, reciprocal actions are taken, operant resources are integrated, reciprocity of exchange is achieved, and value co-creation of the service occurs. S-D logic FP10, which states that "value is always uniquely and phenomenologically determined by the beneficiary" depends on the context in which the beneficiaries—that is, the recipients—are located (Vargo and Lusch 2008). As mentioned earlier, a streamer does not simply stream live gameplay but also includes an appeal to his or her personality and multifaceted nature in the stream. Therefore, the services received by beneficiaries (i.e., viewers) are unique to each streamer, reflecting the streamer's personality and other qualities. The context in which a viewer is located also varies. Thus, each community composed of streamers and viewers can be considered to have unique characteristics. PWYW donation behavior may also reflect these characteristics, and the characteristics of PWYW donation behavior likely differ from one community to another.

Streamers may share similar characteristics, such as comparable personalities. It is also possible that viewers within the community are placed in a similar context, as the community consists of viewers who gather around the same favorite streamer. Therefore, we hypothesize that unique groups related to PWYW donation behavior can be extracted from communities where value co-creation occurs. The relationships among the communities described thus far are shown in Figure 2. Based on this, we propose the following hypotheses:

Hypothesis: Communities comprising streamers (sellers) and viewers (buyers) can be classified into groups based on the characteristics of their PWYW donation behaviors.

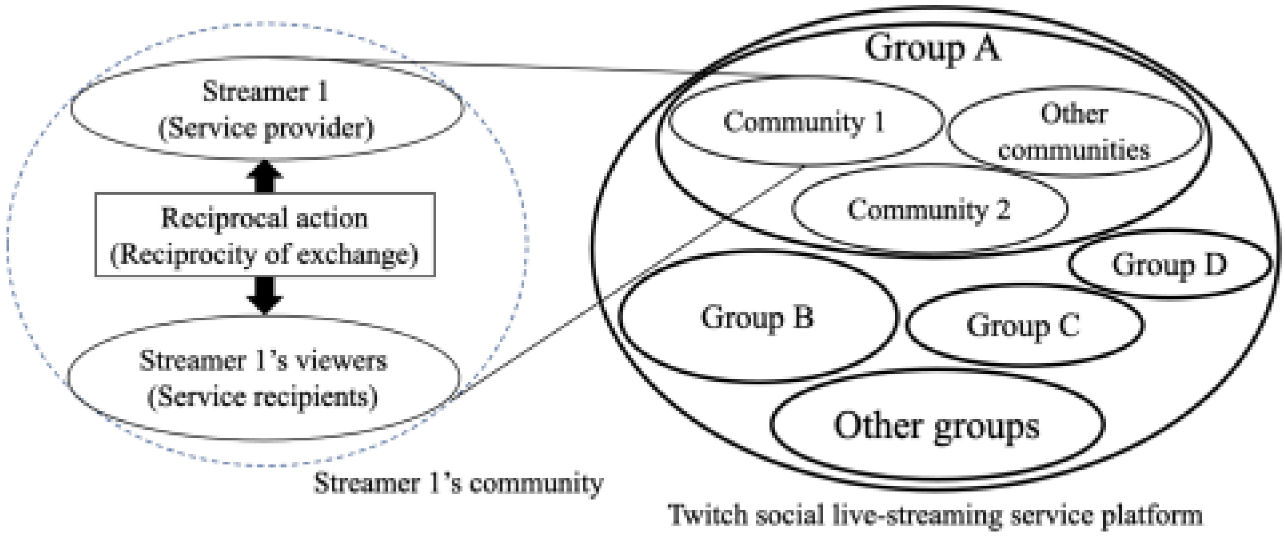

Figure 2: Examples of classification on basis of community characteristics.

METHOD

Data Collection

Twitch streamers eligible to receive donations are referred to as partners. In 2020, there were more than 50,000 Twitch partners (TwitchTracker.com 2021). Partners are ranked based on the number of subscribers, and this ranking is updated daily on TwitchTracker.com. The authors extracted the number of gifted subscriptions (an indicator of PWYW donations) and hours streamed (an indicator of streamers' efforts) from monthly data, as these metrics might be zero for a specific week or day. Accordingly, the number of concurrent viewers—an indicator of the viewers' efforts—uses the average monthly count per hour. In addition, there was a period of turbulence in partner rankings lasting several months, beginning in May 2020, following the global lockdown implemented in April 2020 due to the COVID-19 pandemic. Therefore, to ensure data stability, we verified partners with a monthly gifted-subscription count in the double digits or higher as of April 2021, the starting point of this study, and discovered that the top 350 partners met this criterion. Thus, the data-extraction period was extended to ensure data stability, spanning a total of 19 months: from six months before to one year after April 2020, which was used as the base month. Hence, out of these top 350 partners, 100 had streamed constantly without breaks during the last 19 months. Finally, we analyzed the data from these 100 streamers.

The authors extracted three types of variable data for these 100 streamers from TwitchTracker.com over a 19-month period (19 months × 100 communities = 1,900 data points for each variable). Variable Y represents the gifted subscriptions received by a streamer in a month, which is considered the count of PWYW donations. Since the data extracted represented donation counts rather than monetary amounts, the analysis focused on the donation count. Variable X represents the average number of concurrent viewers accessing the streamer channel per hour per month. Variable W represents the number of hours a streamer streamed in a month.

Variables for our study	Mean value	Standard deviation	Minimum value	Maximum value
Monthly gifted-subscription count per streamer (Y)	2,649	3,011	37	33,869
Average monthly concurrent viewers per streamer (X)	9,259	12,200	251	101,591
Monthly hours streamed per streamer (W)	177.0	94.3	9.6	742.6

Table 3: Variables statistics.

The mean, standard deviation, minimum, and maximum values for each of the 1,900 data points across the variables are listed in Table 3. The difference between the minimum and maximum values was large, and the standard deviations for Y and X exceeded their respective means. This variation reflects the significant differences in characteristics among the communities.

A standardized scatter plot of the variables Y, X, and W is shown in Figure 3 to facilitate direct comparison. Most of the 1,900 data points were concentrated in the central area; however, some were far from the center. In data science, particularly when constructing models such as those for image recognition or accident prediction, extreme outliers are removed, and data contributing significantly to the model's construction are extracted for analysis. However, as the purpose of this study was not to construct an accident-prediction model or similar type of model but rather to analyze the characteristics of PWYW donation behavior in communities of streamers and viewers, it is necessary to analyze whether data outside the center region are meaningful. The characteristics of these community, comprising streamers and viewers, may have contributed to the data falling outside the central area. Therefore, we analyzed the data well outside the center without excluding them.

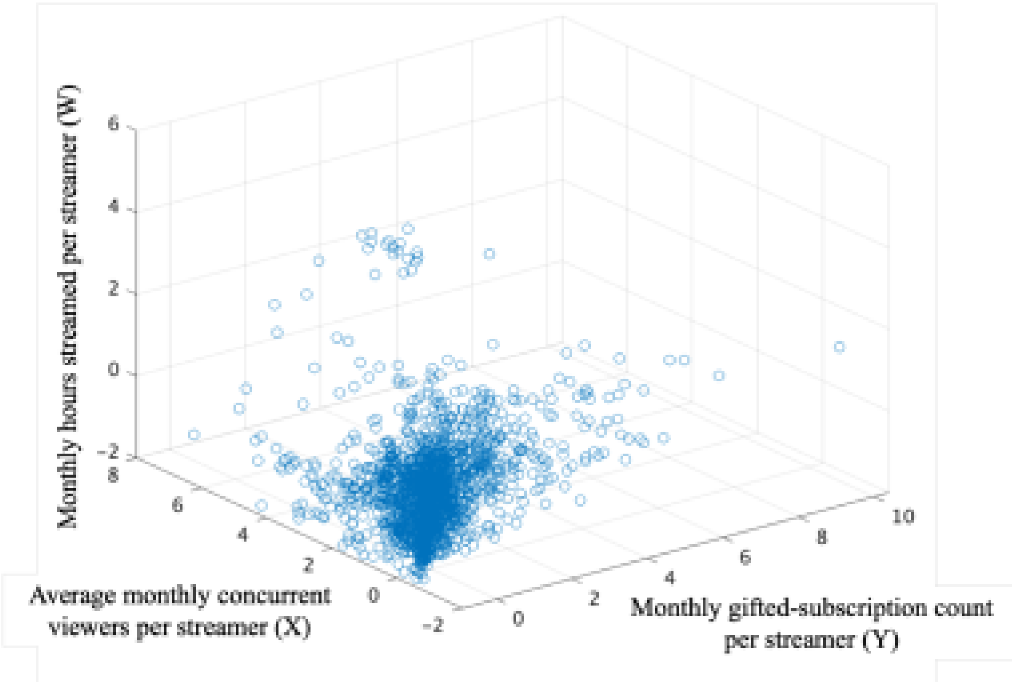

Figure 3: Scatter plot with standardized data for variables Y, X, and W.

Cluster Analysis

We used k-means clustering as the cluster analysis method, a widely used approach in social media and machine learning research (e.g., (Ebrahimi 2022)). The k-means clustering algorithm iteratively assigns data points to k clusters until the clusters' center of gravity stabilize, under the assumption that the data scattered in a certain space and within close proximity are in the same cluster. When conducting k-means clustering, the number of clusters (k) must first be determined; however, as in this study, it is usually unclear how many clusters can be classified. In such cases, the Bayesian information criterion (BIC) can be calculated based on the collected data to determine the optimal value of k (e.g. (Maree and Heerden 2020)). The BIC can be expressed using the following equation:

$$\mathrm{BIC} = -2\ln(L) + k\ln(\mathrm{n}), \quad (1)$$

where, ln is the natural logarithm, L is the likelihood function, n is the number of data points, and k is the number of clusters. When calculating the BIC for a given k, the value of k that minimizes the BIC is considered the optimal number of clusters for the dataset. The following procedure was used for cluster analysis.

1. The center-of-gravity coordinates were obtained from the 19 coordinate data points of each community, as shown in the scatter plot in Figure 3. A new scatter plot (Figure 4) of the center-of-gravity coordinates for 100 communities was created.

2. Based on the scatter plot in Figure 4, we assumed 10 different k values, ranging from 1 to 10, and calculated the BIC to identify the appropriate k for the collected dataset.

3. Using the appropriate k obtained from the BIC, the 100 center-of-gravity coordinates were clustered and grouped on a scatterplot using k-means clustering.

MATLAB R2023a version is used as the cluster analysis tool.

FINDINGS

Results of Cluster Analysis

To represent the 100 communities by their respective center-of-gravity coordinates, these coordinates were derived from the 19 data points corresponding to each community. A scatter plot visualizing the 100 center-of-gravity coordinates is presented in Figure 4.

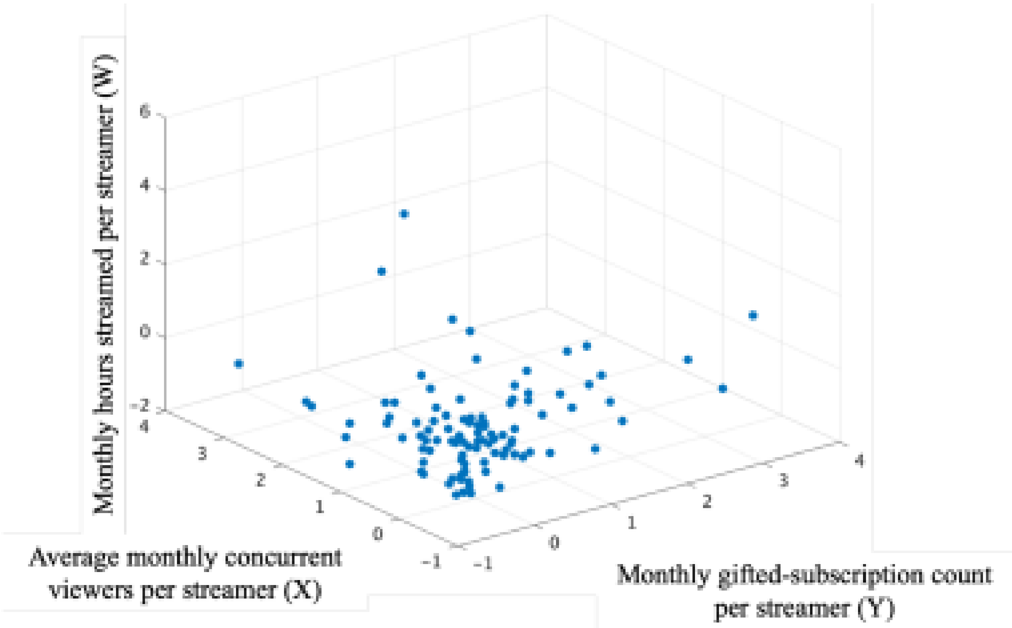

Figure 4: Scatter plot of center-of-gravity for 100 communities.

For these 100 center-of-gravity coordinates, the BIC was calculated for 10 different k values, ranging from 1 to 10; the results are displayed in Figure 5.

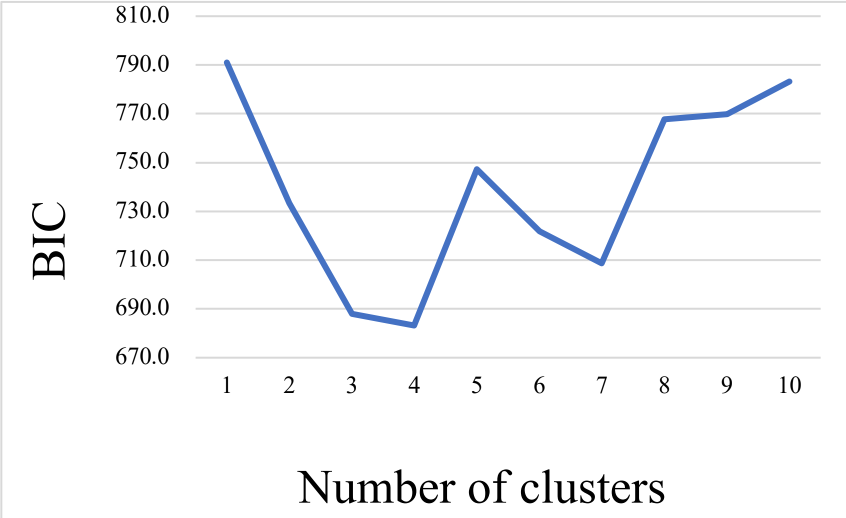

Figure 5: Relationship between BIC and number of clusters based on collected data.

The BIC was smallest at k = 4, indicating that a group of 100 datasets, each containing the center-of-gravity coordinates of 100 communities, was appropriate for clustering into four groups. Therefore, clustering was conducted using k-means clustering in MATLAB with k = 4 to classify the datasets into Groups A, B, C, and D. The number of communities and the center-of-gravity coordinates for each group are listed in Table 4. The 100 centers of gravity in the scatter plot in Figure 4 are classified into Groups A, B, C, and D, as shown in Figure 6. The size of the spheres in Figure 6 is larger than those in Figure 4 because it is difficult to discriminate between groups when the size of the sphere indicating the center of gravity is small.

Group	Number of communities	Coordinates of center-of-gravity for each group		
		Y	X	W
A	63	-0.364	-0.355	-0.186
B	15	0.029	1.715	-0.542
C	15	0.586	-0.026	1.254
D	7	1.959	-0.424	0.151
TTL	100	N/A		

Table 4: Number of communities and center-of-gravity coordinates for each of four groups.

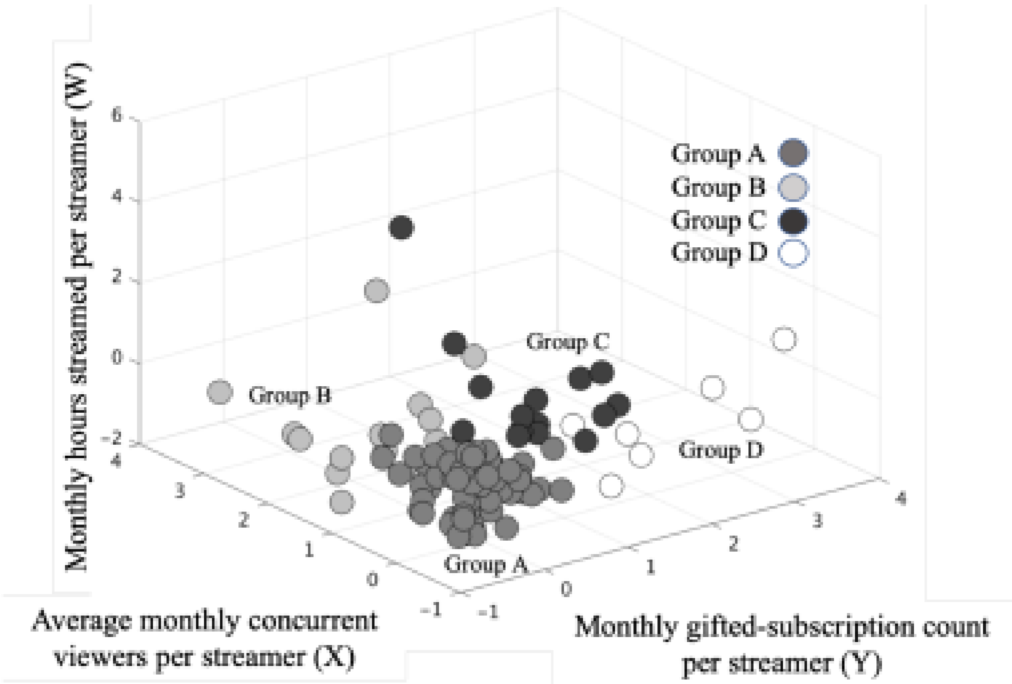

Figure 6: Scatter plot of 100 communities grouped into 4 groups.

Analytical Finding of Testing Hypothesis

Based on Table 4 and Figure 6, the characteristics of each group were analyzed.

According to Table 4, the coordinates of the center of gravity for Group A were almost zero for Y, X, and W, indicating that they were slightly below the average. The coordinates of Group B were negative for W, whereas those of Y and X were positive. The X coordinate, that is, viewers' efforts, is approximately twice the standard deviation, the highest among the four groups, whereas W is approximately minus 0.5 times the standard deviation. The coordinates of Group C were negative for X, whereas those of Y and W were positive. The W coordinate, that is, the streamers' efforts, is approximately 1.3 times the standard deviation, which is the highest among the groups. In Group D, Y is the standard deviation approximately twice, the highest among the groups, even though X and W were not significantly different from those in Group A.

Figure 6 shows that Group A is concentrated near the approximate origin of the coordinates. Group B is located on the left side, where X is larger than that of Group A, which is toward the left. Group C is positioned where W is higher than that of Group A, which is toward the upper side, and where Y was higher, placing it toward the right side. Group D is located where X and W are almost the same as in Group A, but Y is larger than in Group A, placing it on the right side.

Considering the coordinates and positions, Group A had a good balance between Y, X, and W. The relationship between streamers and viewers is stable; streamers' services, viewers' support, and PWYW donation behavior are ideally cyclical, driven by the synergy of mutual efforts from both parties, and their relationships are interdependent. The reason the coordinates of Group A are slightly below zero for Y, X, and W is thought to be the presence of communities in other groups with higher values for each.

Group B exhibits one-sided efforts from viewers to promote PWYW donation behavior, despite low effort from streamers. The relationship between the two sides is reciprocal, based on a strong one-sided contribution from viewers. We assume that the large number of concurrent accesses in Group B makes posting messages and expressing emotions in the chat window more competitive, thus increasing PWYW donations owing to social density. In other words, PWYW donation behavior is likely to be promoted to maintain viewers' presence because they feel that the amount of PWYW donation is low, and are more likely to interpret objects in simple and concrete terms. This group is likely to generate more revenue from fan activities outside PWYW donations.

Group C made a one-sided effort by streamers to promote PWYW donation behavior. The relationship between the two sides is reciprocal, based on the streamers’ strong, one-sided contribution. From the S-D logic perspective, since the streamer only offers a value proposition, it is assumed that viewers make PWYW donations because they find value in Group C streamers’ multifaceted and lengthy live streams. Analyses using UGT by Sjöblom et al. and Hilvert-Bruce et al. suggest that the desire to belong to a community is the motivation behind donations. Therefore, viewers perceive value in the streamers’ services, and the desire to belong to that community, as described by UGT, drives PWYW donations.

Group D had the unique characteristic of promoting PWYW donation behavior, even though there was no significant trend for either X or W. We observed these characteristics by watching live or archived videos of each streamer on Twitch (Twitch 2021) for approximately two hours. The results confirmed that Group D streamers offer a unique live-streaming experience that deviates significantly from typical live-streaming gameplay. For instance, one streamer had DJ and lighting equipment used in discos in the room and was DJ’ing live. Another streamer transformed his room into a quiz contest hall and held a quiz game with the viewers. Thus, in Group D, a reciprocal relationship between the streamer and viewers appears to have been established, with PWYW donations driven by unique streamer activities. As with Group C, it can be assumed that viewers find value in streamers’ services, and the desire to belong to that community through UGT drives PWYW donations. However, the most significant difference from Group C is that X is about minus 0.4, the lowest among the four groups, and PWYW donations are promoted under the least influence of social density. This indicates that the streamers are unique, and their strong personalities promote PWYW donation behavior.

Finally, a typological analysis of the collected data using cluster analysis enabled the classification of communities composed of streamers and viewers into groups based on characteristics related to PWYW donation behavior. Thus, this hypothesis was supported.

DISCUSSION

General Discussion

Previous typological analysis studies using Twitch as a case study have analyzed viewers' user engagement with streamers but did not focus on PWYW donation behavior. Studies that analyzed viewers' PWYW donation behavior, however, did not consider the characteristics of communities composed of streamers and viewers. In contrast to these studies, cluster analysis using actual service data from Twitch's top 100 streamers enabled us to classify the 100 communities into four groups (A, B, C, and D) based on characteristics related to PWYW donation behavior. However, the existence of Group A is not entirely novel compared to prior studies, and we assume that the important finding of this study is the discovery of Groups B, C, and D.

Groups B and C are communities in which the efforts of viewers or streamers strongly drive PWYW donation behavior one direction or another. We suggest that online service platformers plan for further monetization by successfully leveraging the one-sided efforts of both viewers and streamers.

We believe that the findings for Group D are highly significant. Group D is the group in which monetization is most promoted, with nearly twice the standard deviation in the number of PWYW donations, despite having concurrent viewers and hours streamed nearly identical to those of Group A. Group D streamers are considered to drive PWYW donation behavior among viewers due to their surprisingly strong personalities and multifaceted nature. Online service platforms should not only plan for further monetization with Group D streamers but also learn from their knowledge, skills, and other operant resources, as outlined in S-D logic.

Theoretical and Practical Implications

Analysis on the part of the service provider using actual service data

This study is unique in that it includes data related to streamers as the subject of a cluster analysis of PWYW donation behavior. In previous studies, only data from the viewers were used to analyze viewers' user engagement and PWYW donation behavior toward streamers.

We assume that behavioral analysis involving multiple actors, such as streamers and viewers (i.e., service providers and recipients), can reveal insights previously undiscovered when analyzed using actual data from both parties. From the perspective of the S-D logic, because value is co-created by multiple actors, it is considered insufficient to analyze only the behavior of a particular actor. Since the onset of the COVID-19 pandemic, the number of people conducting business in the virtual world has increased (e.g., (Lochner 2021)). For instance, there has been a rise in streamers and YouTubers who are live or video streamers, personal shoppers selling goods, and small e-commerce live corporations selling products through live streaming. This trend is expected to continue. When analyzing such businesses, we assume that data from the service provider is also available. Therefore, discoveries can be made when data from both service recipients and providers are clustered together.

Marketing tailored to community characteristics

This study found that Group B was the most likely to engage in enthusiastic fan activity toward streamers. Considering a group of enthusiastic fans is more likely to contribute significantly to revenue than PWYW donation behavior, we suggest online services should be designed specifically for such communities. Group B also had the largest number of concurrent viewers, as shown in Table 4, indicating the viewers' strong effort. Therefore, the chat window can be considered "fast moving chat rooms" (Hilvert-Bruce, et al. 2018). In this competitive and interactive environment, the best way for fans to stand out is by making PWYW donations. However, a new user interface can be added as a service for fans, such as one that provides viewers who purchase streamer merchandise with a special electronic ticket. When the ticket is entered from the chat window, the text message or “emote” posted will be prominently displayed in a large font or remain visible for a few seconds, rather than flowing. This would increase fans’ enthusiasm and increase greater purchase of goods or PWYW donations. If communities can be classified based on the characteristics of their PWYW donation behavior, it will be possible to conduct targeted marketing activities that generate revenue from viewers who engage in enthusiastic fan activities.

CONCLUSION

We focused on PWYW donations, which were introduced to various online services following the COVID-19 pandemic, and used Twitch as a case study for a typological analysis of PWYW donation behavior among streamers and viewers, based on its unique characteristics. The analysis revealed that the 100 communities of the top 100 streamers could be classified into four groups, based on the characteristics of their PWYW donation behavior. The results also provide both theoretical and practical implications for future studies on monetization. We will continue to analyze PWYW donation behavior among streamers and viewers in the context of the digital twin and metaverse era.

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