Annals of Operations Research (2023) 325:743–765
https://doi.org/10.1007/s10479-022-05062-y

ORIGINAL RESEARCH

Who's watching? Classifying sports viewers on social live streaming services

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Accepted: 2 November 2022 / Published online: 3 December 2022

Abstract
The newly emergent social live streaming services (SLSSs) provide the sport consumers with a synchronised and more interactive viewing experience. In order to help the sport SLSSs firms understanding and engaging with the viewers effectively, this research aims to classify the sports SLSS viewers based on their engagement behaviour, and identify the perceived value and value contribution of each group of viewers. Firstly, 52,545 sports SLSSs viewers' viewing duration time is predicted by a feedforward neural network. Second, the predicted viewing duration time and other extracted viewer behavioural data (number of messages, number of virtual gifts, and value of virtual gifts) are analysed through two-step clustering in SPSS, and classified viewers into four types. Semi-structured interviews were then conducted to understand how each type of viewer co-creates value. The results identified four groups of viewers, namely content consumers, super co-creators, co-creators, and tourists, and identified their distinct value co-creations and perceived value. This study sheds light on combining engagement behaviour and value co-creation literature to classify the sports viewers in the context of SLSSs. This understanding assists the decision-making processes of marketers and operators to promote viewers' co-creation effectively.

Keywords Social live streaming services · Value co-creation · Viewing engagement behaviour · Neural network · Sports viewers classification

1 Introduction

The absence of live sport throughout the COVID-19 pandemic has been felt strongly by sport fans across the world. Most major sporting events at the international and national levels have been cancelled, delayed, or played in empty stadiums. Fans have been missing out on the physical game that offers communal experiences. The entire sports ecosystem needs new ways to deal with threats to fan attendance and engagement. However, video streaming

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presents new opportunities to generate revenue and maintain fan engagement. In response to this COVID-19 crisis, sport event organisers have adopted social live streaming services (SLSSs), such as YouTube and Facebook live, to supercharge the fan communal experience through providing rich, real-time, and immersive experiences of watching events online (Kim & Kim, 2020). In 2020, Twitch attracted 7 million unique streamers, with over 30 million followers, who create and stream sporting events and games on the platform (Twitch, 2020). Therefore, live streaming platforms are not just an extra stream of revenue, but play a central role in connecting with all ages of fans during crises (Neureiter, 2021).

Compared with the traditional social media that uses second screens to interact, these newly emergent services provide the sport event consumers with a synchronised viewing experience (Lu & Chen, 2021). The sport viewers can interact in real time with streamers and other viewers when they are watching the sport events through sending real-time messages and sending virtual gifts to express their personal feelings about a sport event instantly (Li et al., 2018a, 2018b; Liu et al., 2022a, 2022b). Given its increasing importance and rapidly evolving nature, sport SLSSs marketers should invest measurement of viewers' consumption behaviours rather than demographic generalizations to acquire, engage, and retain customers sustainably (Westcott et al., 2018). The topic of conceptualising the types of users and their distinctive engagement behaviours in the context of online communities has been investigated extensively (Y. An et al., 2018; Liu et al., 2015; Westcott et al., 2018). For example, Wu and Yu (2020) revealed four groups of consumers who browse for information, adopting recommendations, consulting reviews, and conducting searches with different levels of goal-oriented or exploratory-based need-states. Van et al. (2016) adopted behavioural data acquired from posts and views from a large multinational corporation to explore the enterprise users' groups and the motivations that underpin their usage behaviour. However, the live streaming communities are relationship-oriented online communities (Cheng et al., 2019) where there exist two levels of social contact—between streamers and viewers, and between viewers (Lin et al., 2021a, 2021b). In this kind of community, the real-time mutual interactions between streamers, viewers, and other viewers are important for facilitating the value co-creation of viewers. In line with the Service Dominant Logic (SDL), customers evaluate and decide the value of other actors' contributions according to the specificity of their usage (Vargo & Lusch, 2008). That is to say that the value is always assessed and determined by the beneficiary based on their value-in-use (Tsiotsou, 2016). Consequently, different types of viewers can contribute to the community and acquire value distinctively according to their engagement behaviour. Given the novelty of SLSSs as a field of research, borrowing theories and concepts from the literature on online communities and value co-creation can benefit our understanding of the types of viewers and their value co-creation that exist in the usage context of SLSSs (Rishika et al., 2013; Singh et al., 2021). Classifying the viewers based on how they utilise the platform can help the sport SLSSs firms understand customer contributions and perceived value, and then engage with the viewers effectively.

Big data is currently available from both firm and consumer activities, making it possible to understand consumer behaviour (Grover et al., 2020; Kunz et al., 2017; Tan et al., 2015; Zhan & Tan, 2020) and consequently formulate more effective customer engagement strategies (Li et al., 2018a, 2018b; Liu et al., 2019; Mishra & Singh, 2018). In this research, we first predicted the viewing duration time and extracted other viewer behavioural data (number of messages, number of virtual gifts, and value of virtual gift) based on large-scale real viewers' behavioural data on sports SLSSs. The predicted viewing duration time and other extracted viewer behavioural data were processed through two-step clustering analysis in SPSS to classify the viewers. 20 semi-structured interviews were then conducted to understand how each type of viewer co-creates value. This study aims to classify the sports SLSS viewers and identify the perceived value of their distinct value propositions. The following research questions underpin this study:

RQ1 What are the groups of viewers that exist in sports SLSSs according to their distinct engagement behaviours?
RQ2 What are the contributions and perceived values of each type of viewer?

2 Literature review

2.1 Definition of engagement behaviour

In the social media literature, the most widely supported conceptualization of social media engagement behaviour is a behaviour-based model (Brooks et al., 2014; Dolan et al., 2016).The activities performed by customers on social media range from merely reading and commenting on posts to posting messages that show different levels of engagement (Vale & Fernandes, 2018). Van Doorn et al. (2010) state that customer engagement is a customer's behavioural manifestations that have a brand or firm focus, beyond purchase, resulting from motivational drivers. Similarly, Vivek et al. (2012) define 'consumer engagement' as the intensity of an individual's participation and connection with the organization's offerings. However, in SLSSs, the virtual gifting behaviour is a mixed function of engagement behaviour that is similar to 'liking' a social media post, but it is in the form of paid virtual gifts (Lu et al., 2018). During the live streaming, a viewer can purchase and send a virtual gift to a streamer to express their emotions. Therefore, the virtual gifting is both a transactional and community-related behaviour. Therefore, this research adopts a holistic definition of customer engagement behaviour provided by Kumar et al. (2010) and defines customer engagement behaviour in sport SLSSs as a mechanism that allows customers to add value both directly (transactional behaviour) and indirectly (non-transactional behaviour) to organisations.

2.2 Typology of customer engagement behaviour on social media

Existing typologies of social media users' behaviours usually categorise behaviours based on two criteria: usage and user types. Among the typologies that classify social media behaviours into usage types based on the engagement level, Muntinga (2011) define these behaviours as consuming, contributing, and creating. These dimensions correspond to a path of gradual engagement with brands on social media, from low (passive) to high (active) activities. Consuming behaviour is where consumers passively receive company—and consumer-related content. The contributing behaviour is the medium level of consumer activity, which reflects the consumer's contribution to a company's content through participation. Researchers pay a lot of attention to consumer actions such as "Like", share, and comment. The creating behaviour includes consumer creation of different types of content. Building on this, Dolan et al. (2016) capture not only the intensity, but also the valence of brand-related activities by considering positively and negatively valenced engagement. Positively valenced engagement levels can be low (consuming), medium (positive contribution), or high (co-creation). Negatively valenced engagement levels can be low (detaching), medium (negative contribution), or high (co-destruction). Uhrich (2014) expand the behavioural view into a customer-to-customer value co-creation context through a series of qualitative research approaches, including in-depth interviews, naturalistic observation, and netnography. He identified five types of customer value co-creation practices: associating and dissociating, engaging and sharing, competing, intensifying, and exchanging. Usage typologies, however, are limited in the sense that the result is largely dependent on the researchers' understanding and interpretation. Meanwhile, users engaging on social media may act out multiple types of behaviours at the same time. A single type of engagement behaviour cannot represent the whole behaviour of a group of users.

The usage typologies are thus oversimplifications of reality, whereas user typologies that classify behaviour into user types are not because they assume people engage in more than a single behaviour at the same time and with the analysis of intrinsic motivations. For instance, Pongsakornrungsilp and Schroeder (2011) focus on value creation in a particular type of co-consuming group: an online football fan community. They demonstrate that consumers can play dynamic roles in the value co-creation as providers (creative posters, brand warriors, and moderators) and beneficiaries. These roles of social media users represent the behavioural nature of social media engagement. Van Osch et al. (2016), based on the core-periphery theory, reveal four groups of enterprise users according to their posting and viewing behaviours. These four groups are core-users, promoters or super-promoters, and peripheral users.

However, the above typologies of customer engagement behaviours are based on the non-transactional behavioural manifestations (Yoshida et al., 2018). SLSSs have emerged as a new form of participatory social media that enables viewers to interact with each other and the streamers. In the study of live streaming services, both the non-transactional and transactional features of customer engagement have been identified (Busalim, Ghabban, & Hussin, 2021;Qian et al., 2022; Lin et al., 2021a, 2021b; Clement et al., 2021). Studies have found that, in general, SLSSs have explored the users' information behaviours, including broadcasting, watching, rewarding, and chatting (Scheibe et al., 2016). Hilvert-Bruce et al. (2018) explain four types of live stream viewer engagement, including emotional connectedness, time spent, time subscribed, and donation, via an international online self-report survey of Twitch users. The donation behaviour is highlighted to be a transactional engagement that represents a customer engagement behaviour of financial donation to the streamer (via PayPal) or charities. Similarly, Lu et al. (2018) highlighted a mixed function of paid virtual gifting, whereby a viewer can purchase and send a gift to a streamer during the live stream. This new and innovative function has led to the emergence of a new monetization model in live streaming.

2.3 Value co-creation of viewers engagement behaviour

Many studies have discussed the reason for customers engaging in different behaviours. In the literature published over the last decade, studies of brand-related social media have been considered both self-directed (consuming) and others-oriented (contributing and co-creating) behaviours (Dolan et al., 2016; Muntinga et al., 2011). In line with the service dominant logic, studies have focused on value co-creations, and suggest that customers access and integrate resources to create value for themselves and others (Akaka et al., 2013).

On the one hand, actors within a system co-create value with their contributions. For example, at a sports stadium, fans and spectators contribute to the atmospherics through their behaviour (e.g., by singing battle chants) and their appearance (e.g., wearing fan merchandise) (Uhrich & Benkenstein, 2012). When it turns to the online community, customers can also contribute to the community, such as by contributing knowledge, comments, and information, by acting as a provider (Pongsakornrungsilp & Schroeder, 2011).

However, on the other hand, although the customer can make the contribution, they cannot create value, but rather value propositions, because the contribution of customers may only be a potential input for the value creation of other actors. According to SDL, actors integrate the service providers' value propositions (competencies and capabilities) to acquire co-created value perceptions (Horbel et al., 2016; Vargo & Lusch, 2016). In this way, the value is always assessed and determined by the beneficiary based on the specificity of their usage, which is called value-in-use (Vargo et al., 2008; Woratschek et al., 2014). Value-in-use is the "customers' experiential evaluation of service proposition in accordance with their individual motivation, specialized competencies, actions, processes, and performances" (Ranjan & Read, 2016: 293). Beneficiaries can acquire a unique perceived use value through enjoying usage (Merz et al., 2018; Ranjan & Read, 2016).

In the SLSSs context, viewers engage with different actors (streamers, other viewers, and the platforms) through gifting and real-time messaging for value co-creation (Guan et al., 2022). For example, viewers sending real-time messages to cheer for players can contribute to the live streaming room atmosphere, which can influence the other viewers' perceptions. Besides, the viewers can also perceive value from other actors' contributions. For instance, viewers watching the players' on-pitch performance listen to the streamer's commentary and discuss with other viewers to acquire perceived epistemic value on SLSSs (Horbel et al., 2016).

Given the fact that the SLSSs are a newly-emerged social media for sport event watching, in the literature there is lack of explanation about viewers' engagement behaviours and related value co-creation in live streaming. The lack of a theoretical understanding of this phenomenon offers an opportunity to explore sport SLSSs. This research seeks to provide insights into the nature and dynamics of typifying consumers' roles based on live streaming usage behaviour.

3 Methodology framework

This research adopts a two-phase approach to address the proposed research question of identifying sports viewers groups and value co-creation (see Fig. 1 below). Phase one is to classify the sports SLSSs viewers based on real behavioural data. In phase one, the viewers' viewing duration time will be estimated by a feedforward neural network (FFNN) model while other viewer behavioural data (number of messages, number of virtual gifts, and value of virtual gift) will be extracted by the statistical functions in Microsoft Excel. The two-step clustering analysis is then carried out to classify the viewers according to the estimated and extracted indicators. Phase two is to unravel the value co-creation of viewer groups in the sport SLSSs. In this phase, a series of interviews with viewers were conducted. The transcripts of these interviews were analysed to obtain more in-depth qualitative insights into the different viewers' self-reported behaviours, and the value co-creation of each group of viewers. The process of this research can be divided into five steps, which are behavioural data acquisition, indicator extraction, viewer segmentation, interview data acquisition, and value co-creation analysis. The analysis procedures are discussed in detail in the following sections.

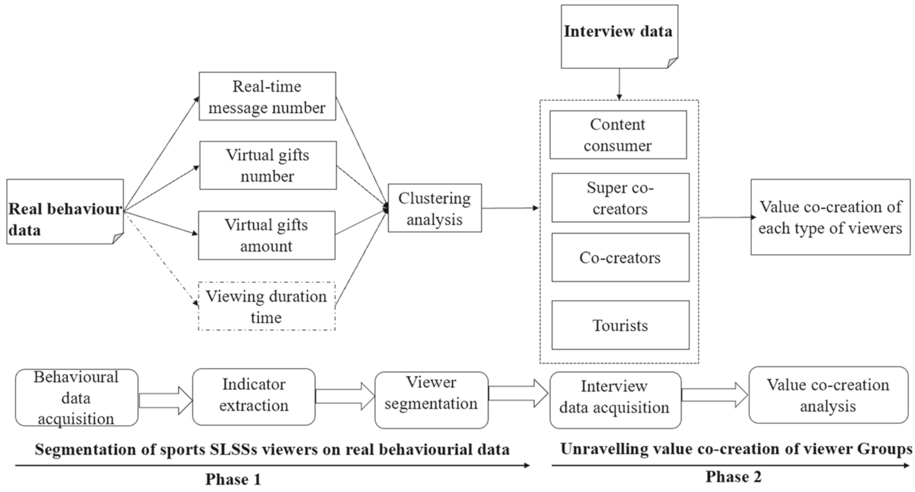

Fig. 1 The methodology framework

4 Cluster analysis of SLSSs viewer groups

4.1 Data acquisition

In the current study, the objective transaction data were used to study sports SLSSs viewers' typologies since real behavioural data can better reflect the viewers' characteristics compared to subjective survey data. The viewer behavioural data from the men's singles finals match (Dec 16th 2019, 20:30 to Dec 16th 2019, 21:40) of a world level competition, the ITTF World Tour Grand Final 2019, were collected from China Sport, which is one of the top sports SLSSs in China. China Sport owns the live streaming copyright for a vast range of world-class sports events including table tennis, billiards (e.g., Snooker and nine-ball), basketball, badminton, fighting, racing, and so forth. China Sport provides high quality live streams of sporting events with an interactive viewing experience on their website, and Android and iOS apps. The collected viewers behavioural data includes viewers' time of entry to the streaming room, real-time messaging time, virtual gifting time, and virtual gifting value. These data were allocated into three separate Microsoft Excel spreadsheets in chronological order. Summary statistics of the dataset are presented in Table 1.

Table 1 Data collected from China Sport

Sheet No.			Content		Amount of ID
Sheet	1ID	Real-time message text	Sending time		3615
Sheet 2	ID	Virtual gifting content	Virtual gifts value	Sending time	3668
Sheet 3	ID	Enter time			88,711

4.2 Indicator extraction

4.2.1 Characteristic indicators of engagement behaviour

In this study, the criteria used to define the clusters are the viewers' overall viewing duration time, the number of messages sent, the number of gifts sent, and the value of the gift's during a single match. Practically, due to the chronological order of the original data, the data were sorted according to the user ID in order to execute the clustering analysis through SPSS.

Firstly, as the match time is from 20:30:00 to 21:20:59 (50 min/3000 s), we deleted the time data of year, month, and day, and recoded the time data in seconds. Some data were incomplete as some viewers had no entry time data but did have interaction data (entered the room before 20:30:00), and some viewers' first interaction data appeared before their first entry data (entered the room more than once). Therefore, we add an entry time of 20:30:00 for these users and defined their number of entries as 1 for better caculation.

Next, a new sheet (sheet 4) in Excel was added in order to merge the same user IDs that appear in the different datasheets into one sheet. Based on the ID in column A of sheet 4, the number of real-time messages sent by each ID in sheet 1 is calculated by the COUNTIF function and allocated into column B. For example, ID '10,718,023' appears six times in sheet 1. This means that ID '10,718,023' sent six real-time messages. Then, in column C of sheet 4, the number of gifts sent by each ID in sheet 2 is also counted by the COUNTIF function. Afterwards, in column D of sheet 4, the value of the total number of virtual gifts sent by each ID was calculated by summing each ID's total gifting price using the SUMIF function. Last, the VLOOKUP function was used to get the number of entrances of each ID in sheet 3 and allocate it to column F based on the ID in column A. In this step, three indicators, namely the number of messages, number of virtual gifts, and value of virtual gift, of each ID have been identified. In total, 52,545 users' behavioural data were prepared for further clustering analysis.

After transforming these data, a vector database is created in Python to store the times of entry, the time of sending real-time messages and virtual gifts, the number real-time messages and virtual gifts, and the value of virtual gifts for each ID. In this way, when searching by a viewer ID, the ID-related data will be returned.

However, it is worth noting that the viewers' leaving times are not recorded by this platform. This impacts the calculation of viewing duration time which is normally calculated by the subtracting the time of entry from leaving time. The reason is that the current SLSSs industry in China is applying PCU (Peak concurrent users) and ACU (Average concurrent users) as the evaluation criteria for operations quality (Pires & Simon, 2015). Therefore, the viewing duration times will be estimated by FFNN model. The following section will introduce the process of estimating the viewing duration time.

4.2.2 Predicting viewing duration time

This section is to estimate the viewing duration time based on the current data. The number of times a viewer enters the stream is n, the first entry time i is t_0, and the second entry time $i + 1$ is t_2 ($1 \leq i \leq n$). In the period between the first entry time, t_0, to the second entry time, t_2, the last interaction time (i.e., sending real-time message or sending a gift) is t_1. However, the viewer may not have an interaction during this period, in which case $t_1 = t_0$.The user's exit time, t_f, must be in the interval $[t_1, t_2]$. The upper bound of the user's viewing duration time is $t_2 - t_0$, while the lower bound of the user's viewing duration time is $t_1 - t_0$. Therefore, estimating the viewing duration time problem is transformed into an estimation of $t_f \in [t_1, t_2]$, and then the viewing duration time can be obtained from $t_f - t_0$ (see Fig. 2 below).

The descriptive statistics of the viewer behavioural data are detailed in Table 2. Among the 52,545 viewers, there are 50,507 viewers with no record of gifting and real-time messaging, which accounts for 96% of the total sample. This proportion is in line with the "80/20 principle", whereby 80% of content in an online community is created by 20% of the users (Van et al., 2016). These 50,507 viewers' behavioural data are lacking t_1 and t_2, which cannot be used to predict their viewing duration through their behaviours directly. Therefore, the average number of real-time messages and virtual gifts of all viewers in a certain period is used to represent the overall behaviour of the viewers in this period.

Figure 3 (Panel A) illustrates the changes in the number of virtual gifts and the changes in the number of real-time massages sent in every 5-min interval. It can be observed that the

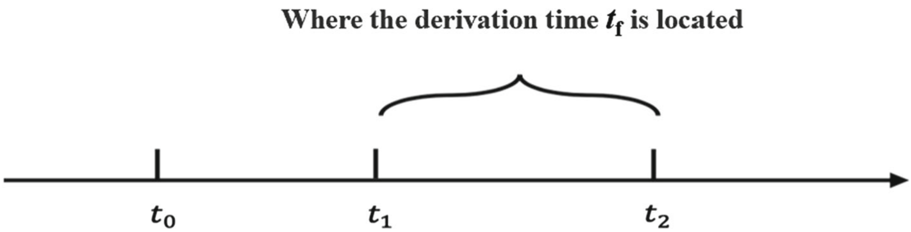

Fig. 2 The timeline of viewer entry time

Table 2 Descriptive analysis

	Total	Mean	Max	Min	σ^2
Entry times	89,289	1.693	47	1	11.11
Number of real-time messages	3614	0.0685	87	0	0.9213
Number of virtual gifts	3667	0.6951	189	1	3.665

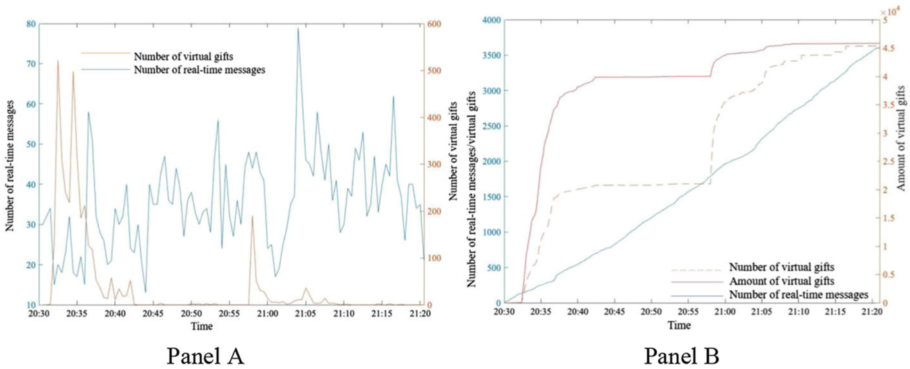

Fig. 3 Trend analysis

real-time messages are more equally distributed than the number of virtual gifts. The real-time messages show peaks in the periods of 20:35–20:37, 21:02–21:05, and 21:15–21:17. On the other hand, the gifts show a concentrated distribution from 20:32 to 20:42, and 20:58 to 21:05. Figure 3 (Panel B) shows the trend of the number of virtual gifts, the number of real-time massages, and total value of the gifts. It can be observed that the trend of the number of gifts is consistently associated with the value of gifts. However, it is also worth noting that the value of the gift may not reflect the viewing time of the viewers, while the number of gifts can indicate the audience's activeness. Therefore, the following analysis does not consider the value of virtual gifts.

According to the results of the descriptive data analysis in the previous stage, 2,038 viewers' data meet the following requirements: (1) entered the live broadcast room at least twice, and (2) had an interaction in the live streaming room (i.e., real-time messaging or gifting). Therefore, these data are used to predict how long these viewers stay in the live streaming room.

The sigmoid function is used to explore the possibility of the viewers leaving the live streaming room from t_1 to t_2. The sigmoid function (Eq. 1) is an activation function of a neural network (Wanto et al., 2017). It has three characters: continuous, differentiated easily, and is a function that does not go down (Pramod, 2015). However, Li et al., (2021) pointed out that visiting duration time of viewers on live streaming platforms is highly correlated with viewers' attachment to the streamers, which can be reflected by the intensity of the interaction. In this study, it is unlikely that the viewers would leaving the live streaming room immediately after having an interaction at t1 (point a), while the probability of users remaining in the live streaming room would decrease gradually when approaching to t2 (point b) (see Fig. 4 below). Therefore, we used the symmetric Sigmoid function (Eq. 2) in this analysis.

$$Sigmoid : s(x) = \frac{1}{1 + e^{-x}}, \tag{1}$$

$$SymSigmoid : \widehat{s}(x) = \frac{1}{1 + e^{x}}. \tag{2}$$

We assume that viewers could be influenced by the overall popularity of the live streaming room based on the following assumption: viewers are inclined to stay when there is attractive

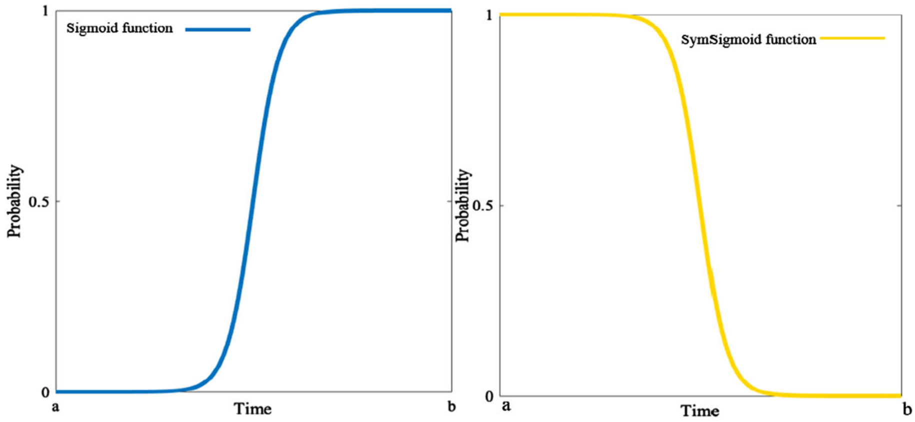

Fig. 4 Sigmoid function and the symsigmoid function

live streaming content, which is reflected by the number of viewers, the number of real-time messages, and the number of virtual gifts at any particular moment in time. Accordingly, three other probability functions are introduced to describe the probability of the users' viewing durations. f(t) is used to measure the probability of continuously staying. The equations are as follows:

$$f_1(t) = \frac{N_2}{N_1}, \tag{3}$$

$$f_2(t) = \frac{N_4}{N_3}, \tag{4}$$

$$f_3(t) = \frac{N_6}{N_5}, \tag{5}$$

$$p(t) = \mathrm{S}(t)\prod_{i=1}^{3} f_i(t), t \in (t_1, t_2), \tag{6}$$

$$t_f = \mathrm{argmaxt} \in (\mathrm{t1}, \mathrm{t2})\, p(t). \tag{7}$$

N2 is the number of viewers who enter the broadcast room at a point in the interval [t1, t2], and N1 is the total number of viewers who enter the broadcast room in the interval [t1, t2]. N4 represents the number of real-time messages sent by the viewers at a point in the interval [t1, t2], and N3 represents the total number of real-time messages sent by the viewers in the live streaming room at [t1, t2]. N6 represents the number of virtual gifts sent by the viewers in the live streaming room at a certain moment, and N5 represents the total number of gifts sent by viewers in the live streaming room at $[t_1, t_2]$. p(t) is used to measure the probability of the duration time t is within the interval $[t_1, t_2]$. The moment when the viewer is most likely to leave the live streaming room is the moment when the probability of the viewer continually staying in the broadcast room is the lowest. We only need to minimise p(t), t $\in$ (t_1, t_2) in order to get the leaving time, t_{f} (Eq. 7). In total, the viewing duration times of 2038 viewers have been estimated. The 50 min of the match time is divided into ten 5-min intervals. And then these viewers were allocated into each of 5-min intervals according to their viewing duration time.

Based on the existing algorithm model and the calculated data of 2038 viewers, the feed-forward neural network (FFNN) is trained to calculate the viewing duration time of the rest of the viewers and set up time labels. The FFNN is comprised of a 5-dimensional input layer, three hidden layers, and a 10-dimensional output layer (dividing the overall match time into 10 5-min intervals) are adopted. The interval range (t_1, t_2) of the rest of the viewers' leaving time can be allocated into the 5-min intervals. The ReLu function (Agarap, 2018) is used as the activation function to extract the nonlinear characteristics of the input vector, and the cross entropy loss function (Martinez & Stiefelhagen, 2019) is used to calculate loss. 90% of the samples were randomly selected as the training set, while 10% were as the test set. The Fig. 5 shows the effect diagram of loss and training accuracy after training:

The accuracy of the training set was improved to more than 90% through multiple iterations of the convolutional neural network, and the accuracy of the original dataset reached 50%. According to the neural network algorithm above and the predicted interval (t_1, t_2) of the leaving time, t_{F}, of all users can be estimated. Then, the designed algorithm, $t_{\mathrm{F}} - t_0$, was used to calculate the viewing duration time of the of the remaining 50,507 viewers.

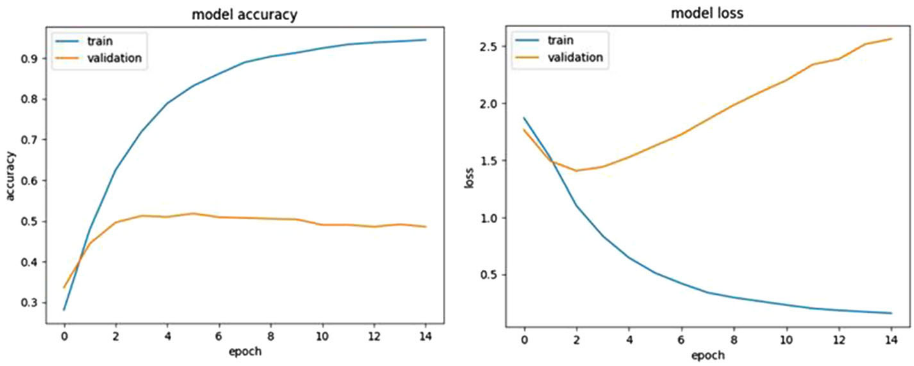

Fig. 5 The training effect of the feedforward neural network

4.3 Clustering analysis

In this research, two-step clustering analysis using SPSS was employed to classify viewers according to the indicators in order to answer the first research question. Clustering analysis is an appropriate research technique for classification as it can identify and classify individuals according to similarities using a set of multivariate statistical techniques (Coppi et al., 2012; Hautbois et al., 2020). It enables both categorical and continuous data to be processed and analysed simultaneously (Hautbois et al., 2020). In this study, because there is a limited quantity virtual gifts and real-time messages, we transferred the data of gifts and real-time messages from continuous data into a categorical scale. The two-step clustering analysis in SPSS can automatically group the dataset based on its algorithm (Van Osch et al., 2016). The two-step clustering analysis involves two steps. In the first step, the software identifies the groupings by pre-clustering. In the second step, the software runs a standard hierarchical clustering algorithm (Norušis, 2011). The Schwarz's Bayesian Information Criterion (BIC) will then define the best solution (Chiu et al., 2001). The BIC is need to above 0.0 and ranges from –1 to 1. It identifies the validity of the within-cluster distance and the between-cluster distance (Norušis, 2011).

The results of BIC indicate there are four clusters, and the value of BIC is between 0.5 and 1, which shows a high quality of the classification (see Fig. 6 below). The four distinct types of SLSSs viewers contained 21,445, 538, 637, and 17,109 viewers, corresponding to 54%, 1.6%, and 43.1% of the total viewers, respectively.

Table 3 below show the descriptive statistics for each cluster. Cluster 1 is the largest group of viewers in the sample, consisting of about 54% of all users. These viewers have the longest average viewing time, which is 36.982 min. However, they do not send real-time massages and gifts. Therefore, they are labelled "content consumers". The second cluster of viewers is much smaller than the first group. This group consists of only 538 viewers, accounting for 1.4% of the total viewers. Although this group of viewers has a shorter viewing duration time (28.19 min) compared to cluster 1, they are actively engaging in sending messages and gifts. On average, each of these viewers sent 77 real-time messages and 538 gifts totalling 63.89 RMB in value. Compared with cluster 1, this group of viewers not only consumes the content, but they also contribute to other actors in the live streaming room by sending real-time messages and gifts. Therefore, we label this group of viewers "super co-creators". The third cluster contains 637 viewers, making up 1.6% of the total viewership, which is just

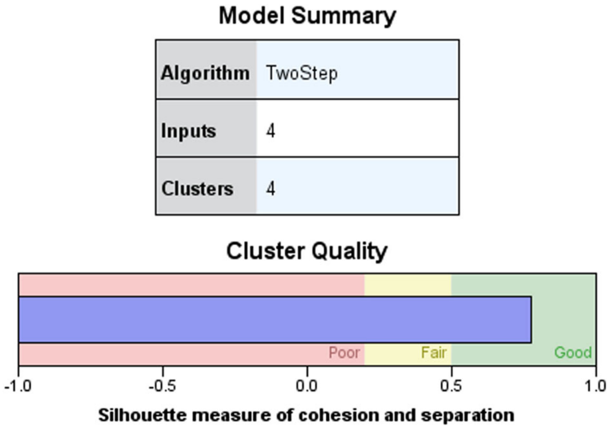

Fig. 6 The test of classification

Table 3 Cluster analysis results

Cluster #	Cluster label	Viewing duration (Min.) AVE	Realtime message (N) Sending	Gifting (N) Sending	Gifting value (¥) AVE	Cluster size (N)	Cluster size (%)
1	Content consumers	36.982	0	0	0	28,374	54
2	Super co-creators	28.198	77	538	63.89	7,356	1.4
3	Co-creators	27.393	637	0	0	8,407	1.6
4	Tourists	1.753	0	0	0	22,646	43.1

slightly higher than that of the cluster 2. Viewers in this cluster have a slightly shorter viewing time (27.393 min) than the second group. Despite being the biggest group that sends real-time messages, they were not sending virtual gifts when watching the sports games on SLSSs. Therefore, we named those in this group "co-creators" who contribute to the community by only sending real-time messages. The last cluster of viewers is labelled the "tourist cluster" as these viewers only spend an average of 1.75 min on viewing the live streaming sports event with no other engagement behaviour. These viewers are like tourists who visit different live streaming platforms but do not stay for long time. It is worth noting that this cluster makes up about 55% of all users of SLSSs.

5 Unravelling value co-creation of viewer groups

5.1 Interview data acquisition

In order to address the second research question and understand the value co-creation in each cluster of viewers, this research adopted semi-structured interviews. Semi-structured interviews were conducted with 20 viewers who are users of China Sport. The interview protocols were developed based on identifying how viewers co-create value with other actors:

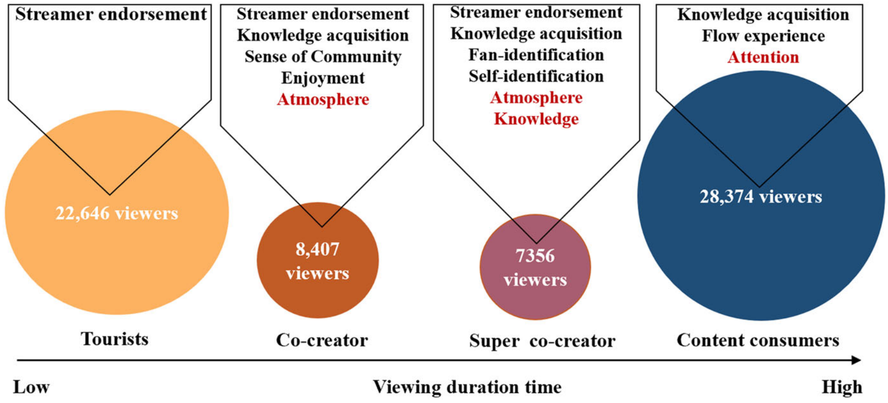

Fig. 7 Understanding the usage behaviours of viewer groups through qualitative analysis

(1) the ways viewers engage in the live streaming room; (2) the motivation and perceived value of engagement. The questions originated from studies that examined value co-creation in a sports context, on social media, and live streaming (Horbel et al., 2016; Kunkel et al., 2017; Pongsakornrungsilp & Schroeder, 2011; Vale & Fernandes, 2018). As the questions were initially developed in English, they were then translated from English to simplified Chinese for this study. The translation steps followed the three stages of translation proposed by Kim et al. (2020). Firstly, two bilingual individuals translated the questionnaire into simplified Chinese. Secondly, another bilingual individual translated the questionnaire back to English. Thirdly, in order to establish the clarity and accuracy of the translated items, three Chinese-English students assessed the discrepancies between the original questions and the translated ones. The researchers interviewed each participant independently through WeChat video calls. The duration of these interviews ranged from 45 to 65 min.

All the interview transcripts were digitally recorded and transcribed into a spreadsheet. In terms of data analysis, the computer-assisted software, NVivo 12, was employed to categorise and decide the representatives of different viewer's clusters (three super co-creators, six co-creators, nine content consumers, and two tourists). The interview results provide further insight into the value co-creation across the four distinct viewer groups. Figure 7 presents a summary of the results. According to the viewing duration time, the content consumers have the longest viewing times, which is followed by the super co-creators and co-creators. These three groups of viewers contribute value propositions to the community and have relatively more perceived value. However, the tourists have the shortest viewing duration and do not contribute to the community. The details of the analysis will be explained in the following sections.

5.2 Value co-creation analysis

5.2.1 Content consumers

The first group of viewers place high value on only consuming the provided content, which in this case is the sport event live streams. Therefore, this group of viewers is labelled "content consumers" who are only consuming the sports event contents while not directly creating any value to other viewers and platforms. Consumers emphasise that the knowledge acquisition and flow experience are their main motivation for viewing the sport event on SLSSs. For example, one respondent emphasised that concentration on the match can help them to gain more knowledge:

> *My original intention to watch the sporting event here is to view and enjoy the players' performances in a focused manner. I don't send messages or virtual gifts as it might distract me. I sometimes even switch off the floating message function, and zoom into the screen to watch the videos, to avoid distractions. Therefore, I can learn how world-class players use skills and tactics to counter the different styles of their opponents and different solve problems in any situation.*

Other viewers explained their behaviour and illustrated the perceived flow experience that is acquired from the new functions of China Sport. For example, one respondent stated that:

> *I enjoy watching games on China Sport by using its new functions, such as the 360 degree and multi-angle views. I like viewing from the player's angle. It makes me feel like I am a VIP who is sitting on the side, and the players are playing just in front of me. I don't send real-time messages, but I do listen to the streamers and sometimes have a look at what other viewers are saying.*

However, although this group of viewers does not contribute directly via real-time messages and gifting, they can indirectly influence other viewers' behaviours and add value to the platform. In the age of the 'attention economy', viewers' attention can be perceived as a kind of product, which is 'eyeballs', to attract advertisements and generate revenue (Webster & Ksiazek, 2012). In the current study, we also found that the content consumers can attract more viewers to enter the live streaming room. On a related note, one participant stated that "When I first came to the platform, I would choose a room with the most viewers. Now, if my favourite streamer is not on live, I would also go for the room with highest number of viewers". This statement implies that viewers enter rooms to seek a sense of community, the strength of which is established by the number of viewers.

5.2.2 Super co-creator

Apart from knowledge acquisition, viewers in the super co-creator referred to their sending of messages and gifting behaviours in several ways. One such way is 'endorsement'—sending virtual gifts and real-time messages to show their appreciation and admiration for the streamers. Another way is 'fan-identification'—sending virtual gifts and real-time messages to show their commitment of the players and teams. The final way is 'self-identification'—commentating on the sporting events by sending real-time messages to express their own knowledge of table tennis and build their reputation in the community.

On SLSSs, the viewers are provided with an opportunity to interact with streamers and other viewers by sending virtual gifts. When viewing the sports live streaming events, the viewers can purchase and send virtual gifts during the game time. The super co-creators share a mutual game experience with one another and create a party-like atmosphere in the virtual online community. Some viewers described sending virtual gifts as a way to show their appreciation and admiration for the streamer in front of all viewers of the stream:

> *I am a fan of 'Xiao Ma Ge' as he is very professional when commentating on sport events. I like to listen to his commentary as I can acquire a lot of knowledge and information from him. I send virtual gifts to him to thank him for his hard work in*

providing useful information and, more importantly, to attract his attention. If he notices my gifts and responds to them, I feel very excited. I think we are very close.

There are also interviewees who stated that sending gifts is a way to cheer and express their support for the players. This is described by one of the interviewees as follows:

I like to send gifts to celebrate when the Chinese team wins a game or when they are playing against a strong opponent. If Liu Shiwen is playing, I would send much more. I am her fan.

In this study, the results also reveal that the super co-creators are concerned with 'self-identification'. The reason for sending real-time messages is to answer other viewers' questions related to techniques, strategies, scores, the players styles, and so forth. This is in line with the view that consumers would like to present themselves in the online community to seek and develop influence and build an identity among the community of viewers (Thorbjørnsen et al., 2007). Due some streamers lacking professional knowledge of the sport, they could not truly satisfy the needs of the viewers who are professional players. Value co-creators want to improve the streamer's level of expertise by commentating on the match. In this way, co-creators not only provide knowledge to the streamers and other viewers, but they can also feel satisfied by gaining a sense of self-identity through self-presentation.

5.2.3 Co-creators

Co-creators have a similar usage duration to consumers and super co-creators in terms of consuming content. However, co-creators do not co-create value in the same way as the other groups of viewers. Co-creators send an abundance of real-time messages to achieve their perceived values. Their motivations for sending real-time messages display some striking differences compared with super co-creators. Compared with super co-creators, co-creators have lower fan identification and less streamer endorsement, but they seek a relatively strong sense of community. A few respondents mentioned that they are not willing to pay for virtual gifts:

I like to engage in the community through sending real-time messages. It makes me feel that I am part of the fan community. For example, when other viewers cheer for players, I would follow them by typing 'go go go', when I see 886 (bye bye) with the streamer's name when the game finishes, I will copy them. I also attend streamers' interactive quizzes by typing '1' or '2' to vote for guessing which player would win prize.

Similarly, other respondents noted that:

I like the atmosphere of everyone cheering together. I think the purpose of live streaming is to get people to watch the games together and cheer. I have national pride. The sense of unity is a very important feeling that the live streaming can bring to me. As I can't be there to support the players, sending a real-time message on the live stream platform makes me feel like I am encouraging them. When I watch live sports platforms, sometimes my message will be selected and read out by the anchors, and I may have some opportunities to communicate with others who are fans like me.

Co-creator also look to acquire knowledge when watching sport live streams. However, they are not only passively listening to streamers, but also sending real-time messages to ask questions. Meanwhile, they are keen to communicate with streamers and other viewers to discuss the players' techniques, skills, and strategies. There is a viewer mention that:

> *If the streamer is a professional in table tennis and I am uncertain about something, I will send my questions by real-time messages. I also interact with other viewers. When the streamers don't answer some of my questions, some viewers answer me by sending real-time messages. I can learn a lot in this way.*

Apart from acquiring professional expertise from watching and interacting, co-creators expect to access more information about the sports equipment or players since such information may not be accessible elsewhere. As one of the respondents stated:

> *I often send real-time messages to ask about a player's background, past achievements, and equipment. In my opinion, this is a good way to get to know information about the players, especially young players.*

Some respondents of the co-creators firmly believe that watching sport events on SLSSs is entertaining. For example, one comment illustrates their perceived value of enjoyment when viewing the sport events on SLSSs:

> *There is a lot of contents in the real-time messages, such as expressions of love and hate between viewers. Although I am not often engaging in such debates, I like to watch other people quarrel.*

5.2.4 Tourists

Tourists describe their behaviour in terms of looking for the right streamers. There can be more than a dozen streamers covering important matches at the same time, and viewers seek to choose a channel selectively to meet their particular viewing needs (Smith et al., 2013). Tourists are the nimblest group who most easily shift between streaming rooms and platforms to optimise content discovery and perceived value. Among those who were found to be tourists, 85% said that they are not very professional at table tennis and are newcomers to China Sport. They explain that they will choose the streaming room with the highest number of viewers at the beginning. They travel around different streaming rooms to try to find a suitable streamer who can meet their requirements. As one respondent stated:

> *At the beginning, I would switch around, but I believe I would stay in one streamer's room when I found a streamer that suits my taste. For me, the first element is to see whether the streamer is good at technical commentary. The second element is the style of the streamer. I would say that for me the importance is weighted at around 70% for their technical skills and 30% for their personality.*

Furthermore, another respondent also mentioned that the appearance and interactivity of the streamers might also be a factor affecting whether or not their streaming room is chosen:

> *When there are no important games on, I flick through different streaming rooms to find a beautiful female streamer. However, I will look for a streamer who is professional in table tennis when there is a semi-finals or finals being streamed.*

6 Discussion

As a newly-emerged type of social media platforms, SLSSs provide the sport event consumers a more interactive community with a synchronised viewing experience. Although conceptualising the user groups and their distinctive engagement behaviours in the context of online communities has been investigated extensively, the distinctions between different sports SLSSs viewer groups remain unknown. This study has shed some light on using customer behavioural big data to classify viewers in the SLSSs and explore the value co-creation of each type of viewer to facilitate operations management and set up marketing strategies.

6.1 Implications for research

The findings of this study have several important implications for research of customer behaviour and value co-creation. Firstly, in this research, we estimate an FFNN model using a dataset of 52,545 viewers' real behaviours from a popular live streaming platform in China to estimate their viewing duration time in this novel business context. Next, by combining the clustering analysis of viewers' behavioural data (real-time messaging, gifting, gift value, viewing duration time) and interviews, this research is the first attempt to investigate and identify the different viewer groups by considering both the non-transactional and transactional features of customer engagement behaviour. The viewers' behavioural data delivered insights into their engagement behaviour and revealed four distinct viewer groups: content consumers—longest viewing duration without real-time messaging and gifting; super-co-creators—relatively long viewing duration with real-time messaging and gifting; co-creators—relatively long viewing duration with only real-time messaging; and tourists—shortest viewing duration time and without messaging and gifting. This is in line with an earlier study on enterprise social media, which found that the majority of content is created by a minority of users. However, different from the 'promoters' identified by Van Osch, et al. (2016), who occasionally post, we found that the first and last group of viewers do not contribute content to the community. The clustering analysis is also an important preliminary step required for exploring the viewers' value co-creation in the context of SLSSs.

Secondly, different from previous studies that simply consider the motivations of engagement behaviour, this study provides an insight into what values different groups viewers perceive from viewing live streams on SLSSs, and how they contribute to platforms and other viewers, through a qualitative empirical study. In line with SDL, this study adds to our understanding of what the value co-creations of different types of viewers are. Thus, this study extended theoretically the boundary of the value co-creation studies into the user segmentation studies in the context of SLSSs.

Furthermore, the findings of this study suggest there exists a novel viewer group—tourists—in the SLSSs setting. They do not contribute to the community but have the potential to transfer into other groups of viewers. The SLSSs should not only consider whether tourists contribute to the community, but rather consider how long they can stay in the streaming room. This is because, just like the content consumers identified in this study, the viewers' attention can attract other viewers. A community on a platform can only boom once there is a consistent source of attention, frequent engagement with the provided content, and contribution of information to the platforms.

6.2 Implications for practice

Segmentation, targeting, and positioning are fundamental to any marketing or brand management strategy. To date, viewers of SLSSs have most frequently been treated as one homogeneous group by marketers developing online promotion strategies. This study reveals that there are at least four distinct segments within the overall sports SLSSs group that can be differentiated based on quantity and quality of usage. This study also has important implications for operations managers of the sport SLSSs, and the streamers on SLSSs. First, the current sports SLSSs industry in China is still lacking uniform standards for service performance. This leads to a problem for sports SLSSs of ineffective behavioural data management and storage. The proposed neural network algorithms to estimate viewing duration time are intended to provide a decision support tool for sports SLSSs firms. Meanwhile, the SLSSs platform should not only use the statistics of page views (PV) and daily active users (DAU) as these parameters can neither reflect the reasons behind the data rise and fall, nor can they be used to explore the real characteristics and value of users. The current study will allow sport SLSSs managers to understand the perceived value and contributions of each group of viewers in order to guide their operation strategy. Secondly, the previous literature has assumed the importance of encouraging people to interact and contribute knowledge to the social media community. This research argues that a large base of the content consumers is important for attracting 'tourists' to enter the live streaming room. Therefore, the sport SLSSs should consider how to increase the content consumers' levels of stickiness and activity. Last, it seems that the tourists do not contribute value to the platforms and other viewers, but they are the potential fan base of the platform. The sport SLSSs could increase the diversity of streamers, as well as improve their level of professional sports knowledge by providing online tutorials.

7 Conclusion

In this research, we set out to investigate the viewers groups in sport SLSSs and their value co-creation by combining web behavioural data and interview data collected from the SLSSs users. This study applies a two-phase approach to address the research questions. The first phase identifies the viewers' groups through clustering analysis of viewers' behavioural data (viewing duration time, real-time messaging, gifting, and gifts value) from a major Chinese sports SLSS. The value co-creation of different viewers groups in the SLSS community is then unravelled using content analysis of the interview data. This study has found four groups of viewers: content consumers, super co-creators, co-creators, and tourists, thus answered the first research question. The distinct engagement behaviours and value co-creation of each of the groups have been analysed in order to address the second research question. We identified a new group of viewers who do not contribute to the sport SLSS community but has high level of streamer endorsement. Therefore, they may be transformed into one of the three other types of viewers by the effort of streamers.

This study has shed light on combining engagement behaviour and value co-creation literature to classify the user groups in the context of SLSSs. This understanding assists the decision-making processes of marketers and operators to enable viewers' co-creation effectively. The main limitation of this study is that there is insufficient data to facilitate an analysis of engagement frequency and live streaming shopping behaviour. Whilst this study does provide some interesting insights, it would be valuable to conduct similar studies with more behavioural data. Quantitative data analysis is also encouraged to define the value co-creation of distinct type of viewers in the future.

7.1 Limitations and future work

In this study, there is a limited amount of gifting and messaging data, so the clustering analysis according to frequency failed. Therefore, future research could adopt approaches that use more behavioural data to analyse the viewers groups in terms of their usage frequency and duration. This would allow managers to design a strategy that is more accurate and effective. In addition, this study used customer behavioural big data from a sport live steaming service. As live streaming shopping has just been introduced by the sports SLSSs industry in China, the viewers' behavioural data related to live streaming shopping is limited in this study. Therefore, future studies could be based on collecting viewers' behavioural data related to live streaming shopping from similar sports SLSSs to examine viewers' groups. Furthermore, the value co-creation of each type of viewer is examined by qualitative data from semi-structured interviews. Although the qualitative data offered enough knowledge of how each type of viewers co-create value in the community, future work may conduct quantitative study (e.g., survey) to provide a more comprehensive understanding.

Both organisations and consumers in the sport context have gradually accustomed themselves to the growing use of live streaming before and during the COVID-19 pandemic. In the future, sport live streaming platforms will adopt all kinds of technologies to improve their business performance and participation performance. Therefore, it is imperative for researchers to attach more importance to the research of the sport SLSSs use and customer engagement.

Acknowledgements Special thanks to China Sport for helping with the empirical data for this paper. We also would like to thank employees at China Sport for their time.

Funding This research was funded by Deng Yaping Sports Scholarship (Grant ID: 16415) and China Postdoctoral Science Foundation (Grant ID: 2021M693038).

Data availability The dataset generated during the current study is not publicly available as it contains proprietary information that the authors acquired through a license. Information on how to obtain it and reproduce the analysis is available from the corresponding author on request.

Code availability The code that supports the findings of this study are available from the corresponding author upon request.

Declarations

Conflict of interest The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Ethical approval The study was conducted and approved by the Ethics Committee of the University of Nottingham.

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