Predicting viewer gifting behavior in sports live streaming platforms: the impact of viewer perception and satisfaction

Abstract

Sports viewers have been offered an unprecedented viewing experience to share their passion with their team and communicate in real-time with a streamer and other viewers by sending messages and virtual gifts on sport live streaming platforms (SLSPs). These activities can reflect viewers' underlying perceptions and levels of satisfaction towards the viewing experience. Using actual viewers' behavioral big data, comprising of 16,204 real-time messages and 5,540 virtual gifts, this study combines machine learning techniques and structural equation modelling (SEM) to examine the influence of viewer value perception on gifting behavior through the mediation effect of satisfaction. The results suggest that satisfaction fully mediates the effects of viewer value perception on gifting amount and partially mediates the effects of value perception on gifting number. Important theoretical and managerial implications of this study for social live streaming service (SLSSs) researchers and practitioners are also discussed.

Keywords: Engagement behavior; Value perception; Social live streaming services; Sports live steaming platforms; Machine learning.

1. Introduction

In recent years, an interactive form of web-based social live streaming services (SLSSs) has grown rapidly worldwide (Needleman, 2015). In western countries, a gameplay-based live streaming platform, Twitch, is currently the largest live streaming platform with over 17.5 daily million active users who can stream, watch, and interact (Twitch, 2020). In China, there are over 200 live streaming apps with a total of 854 million users and 100 million monthly active live broadcast users (CNNIC, 2019). Chinese users have adopted live streaming for all types of applications, including pan-entertainment of singing, dancing, playing musical instruments (Su et al., 2020), e-commerce (Wongkitrungrueng & Assarut, 2018), and the sharing of personal knowledge and experience (Lu et al., 2018).

Given this trend, IT giants have established sports live streaming platforms (SLSPs) to diversify revenue streams. SLSPs, as a new type of SLSSs, offer sports fans with a series of new functions, such as a 360-degree view, multi-screen display, and a virtual reality environment, to create an intensely exciting viewing experience. SLSPs also provide a unique viewing experience that enables fans to share and affirm their devotion to their sports or teams with other online fans. Besides, SLSPs enable viewers to choose their favorite streamers' rooms and interact with them instantly by sending real-time messages (He et al., 2017) and virtual gifts (Scheibe et al., 2016). Previous studies on SLSSs have found that live streaming content was created by the streamers (Friedländer, 2017; Lu et al., 2018). However, SLSPs depend on sporting events, which cannot be created by streamers. In addition, the profit model for the Chinese SLSSs industry is mainly divided into three types: value-added services (virtual gifts), traffic monetization (advertising), and e-commerce. Compared with the general SLSSs and game platforms, SLSPs mainly rely on virtual gifts for revenue. Therefore, how SLSPs can stimulate the consumption of virtual gifts during live streaming remains an important area of research.

Existing literature on SLSSs has mainly focused on addressing the issues of adoption (Hou et al., 2019), user engagement (Lu et al., 2018), motivations (Hilvert-Bruce et al., 2018), and psychological consequences of SLSSs (Kim & Kim, 2020) based on survey data. Despite these critical insights, there is a lack of studies investigating how firms can utilize big data to understand online viewers' engagement behaviors (Clement et al., 2021). In recent years, social media analytics have been used increasingly in marketing studies. According to Tse et al. (2019), it is crucial for any firm to consider its downstream supply chain and meet customer needs. Using machine learning can help companies to evaluate big data from the public domain and enable the quick identification of customer opinions at the source (Fan & Gordon, 2014; Tan et al., 2015; Tan et al., 2017; Zhan & Tan, 2020). Therefore, obtaining a deeper understanding of behaviour and value perception through viewers' big data insights is beneficial to the SLSPs for refining their marketing strategies in terms of facilitating consumption. The theory-driven analytical approaches such as structural equation modelling (SEM), which can examine the causal relations among variables, has long been used in customer research. Literature in this domain, however, lacks the adoption of machine learning approaches to identify proxies of constructs for conducting SEM in customer behaviour research.

By combining machine learning techniques and SEM, this study fills the research gap and explores the relationship between viewer value perception and gifting behavior on SLSPs. The following research questions underpin this study:

RQ1: What are the viewers' most common topics of conversation when spectating sports events on SLSPs overtime?

RQ2: What are the viewers' overall sentiments towards watching sporting events on SLSPs overtime?

RQ3: How does value perception impact gifting behaviors through the mediator of satisfaction SLSPs?

The remaining sections will, firstly, review related literature and discuss the chosen research method. Next, the analysis and results will follow, and finally, a conclusion and a discussion of the implications of this study will be presented alongside to suggest avenues for future research.

2. Literature review

2.1 Social live streaming services

SLSSs are perceived as a primarily synchronous social media form, which differ from traditional social media such as Facebook and Twitter (Scheibe et al., 2016). One feature of live streaming lies in the social aspect, that is, the real-time interaction (Hou et al., 2019). In a live streaming room, viewers can post real-time comments to engage with the streamer and other viewers. Another unique feature of SLSSs is based on the new monetization model – the consumption of virtual gifts. It is visible to both the streamer and all viewers what the gifts are, by whom they are given, and the total number of gifts received by the streamer during an event.

This research starts with a systematic literature review on SSLSs. A Boolean search was conducted based on the terms ‘social live streaming services’ and ‘live stream’ from four databases: Elsevier Science Direct, Ebsco, Google Scholar, and Scopus of Elsevier. The articles obtained from the database searches were first scrutinised based on their titles, keywords, abstracts, which produced a list of selected articles whose full content was carefully reviewed. We found that over the last three years, the body of research on social live streaming service has been growing, which indicates live streaming is an important research focus. Based on the research questions of our study, a total of 20 existing studies were selected and compared with the current study in terms of their methodology and key findings (Table 1). The existing studies on SLSSs can be divided into topic-specific SLSSs (e.g., Twitch for gaming), general SLSSs (without any thematic limitation), and s-commerce (social-commerce, developed from e-commerce).

[Please insert Table 1 about here]

The majority of these selected studies focus on general SLSSs and s-commerce. They address the issues of understanding what impact users' consumption and usage intentions, including trust (Wongkitrungrueng & Assarut, 2018; Guo et al., 2021; Hsu & Lin, 2021), flow experience (Chen & Lin, 2018; Li et al., 2018; Hsu & Lin, 2021), endorsement (Chen & Lin, 2018), servicescape (Chen et al., 2020), perceived value (Wongkitrungrueng & Assarut, 2018), and social interactions (Su et al., 2020; Wan & Wu, 2020; Lin et al., 2021; Clement et al., 2021). Studies on topic-specific SSLSs can be further divided into video games and sports events. The literature on video games live streaming has explored the pull and push factors of the e-sports viewers' motivations (spectatorship motivation and socio-motivation) for encouraging live stream engagement behavior (Hilvert-Bruce et al., 2018; Kim & Kim, 2020). There is a study that measured the mediation role of e-sports content live streaming consumption in the relationship between e-sports recreational gameplay behavior and the intention of e-sports event broadcast consumption (Jang et al., 2021). Studies on sports event live streaming are emerging as the sports events' media products are assimilated into live streaming services. For example, taking National Football League (NFL) live streaming on Twitch as a case study, Qian (2021) confirmed that viewers' continuous spectating intentions are positively impacted by virtual interactions. However, these studies measured users' behavioral intentions using interviews and surveys rather than examining users' actual behaviors by using behavioral big data (Qian et al., 2020; Hedlund, 2014).

Today, customer-generated content usually contains valuable information about customers' experiences with a product or service. Big data analytics such as text, data mining, and machine translation, can provide useful insights by evaluating large scale datasets to identify the customer opinions rapidly and allow the service providers to refine their marketing strategies accordingly (Fan & Gordon, 2014; Zhan et al., 2018). Machine learning techniques and big data analytics are well-adapted to the Computer Sciences field. They allow researchers to address large quantities of data and explore information from those datasets (Shan et al., 2017; He et al., 2017). However, only two studies have adopted actual customers' behavioral big data to explore s-commerce and general SLSSs live streaming consumption behavior (Clement et al., 2021; Lin et al., 2021). They tested the influence of likes, chats, visits, exposure time, and streamers' emotions on the intended purchasing behavior. With actual behavioral data, these studies explored viewers' real experiences of engagement and purchasing behavior, which cannot be examined through surveys or interview-based datasets.

Nevertheless, despite these critical insights, little research has focused on utilizing real-time big data to understand the impact of viewer value perceptions on viewer engagement behavior on SLSPs. To fill these gaps, our study aims to address the issue of how viewer satisfaction mediates the relationship between viewer perception and gifting behavior on SLSPs during the event by analysing actual viewers' behavioral big data.

2.2 The operations mechanism of sports live streaming platforms

SLSPs, as one of the newly emerging topic-specific SSLSs, focus on providing viewers with live streaming sporting events and other sport-related content. SLSPs have a unique operating mechanism with distinctive features in comparison to other types of live streaming platforms. Fig. 1 illustrates the mechanism of SLSPs with related features.

[Please insert Fig. 1 about here]

Different to general SLSSs and e-sports where diverse videos are generated in real-time by streamers based on their own experience of playing video games, eating food, painting, dancing, and so on, SLSPs rely on the broadcasting right of the sporting events (Lu et al., 2018; Qian et al., 2020; Kim & Kim, 2020;). In the content production step, the original contents are sporting events. The sporting events are produced by players, teams, events operators, and other stakeholders of the events. Once SLSPs obtain the exclusive full live streaming rights for a particular event, they can then be provided with the event's signal – the content authorization step. At the third step – content reprocessing – individual users who register as free-streamers (who earn money by receiving virtual gifts) or approved as contracted streamers (who get paid by the platform) set up their own streaming rooms and broadcast the same sporting event with the provided signal. In this step, the SLSPs streamers commentate on matches, and address viewers' questions using their voice, appearance, and knowledge of the sports matches (Kim & Kim, 2020). Thus, the streamers reprocess the provided sporting content. At the last step, the reprocessed content is diffused to the viewers in every individual streaming room. SLSPs offer sports fans with a real-time interactive and active spectatorship experience. Traditionally, viewers cannot participate in the broadcast when watching live streams on TV, but can only passively accept the interpretation of the event by the anchor (Smith et al., 2013). Sports fans on SLSPs are not only watching the event, but also embedded in the live streaming process to cheer for their teams or to criticize opponents with streamers and other audiences by posting real-time messages (Fan et al., 2018) or virtual gifts (Scheibe et al., 2016) (see Fig. 2).

[Please insert Fig. 2 about here]

On SLSPs, real-time messages generated by viewers are shown in the open viewer chat. Meanwhile, these messages are automatically animated over the stream screen, which is called Danmu (Fan et al., 2018), offering an immersive experience for viewers (Lu et al., 2018). Apart from sending real-time messages, viewers are offered the opportunity to send both free gifts and paid gifts when watching a live stream. Sending free gifts is similar to 'liking' a post on social media, but with a different visual design (e.g., red packets and roses). Viewers send free gifts to show their appreciation to the streamer, or simply express their emotions towards a wonderful shot played in the sporting event. The paid gifts on SLSPs, on the other hand, are different from the donation system on Twitch, as the latter does not show the donation content on the screen (Hilvert-Bruce et al., 2018). On SLSPs, paid gifts with different animated shapes are displayed to all viewers on the stream. The viewers normally purchase virtual gifts via online payments and send them to catch the streamer's attention in case their real-time messages are not noticed (Lu et al., 2018). The virtual gifts sent by viewers can be exchanged into cash, which is split between the streamer and the platform (Hou et al., 2019).

2.3 Theoretical background and hypotheses

2.3.1 The Stimulus-organism-response (S-O-R) model

The S-O-R model was originally developed in environmental psychology (Mehrabian & Russell, 1974). It suggests that the stimuli (S) in an environment affects people's internal or organismic states (O), which in turn facilitate their behavioral response (R). Using the S-O-R model in consumer behavior studies helps understand the impact of shopping, as an environmental stimuli, on consumers' behavior. So far, this model has been used to explain offline and online shopping behavior (Luqman et al., 2017; Kaur et al., 2017; Arora et al., 2020). For example, Peng & Kim (2014) used the S-O-R model to determine that both consumers' internal motivations and external website factors involved in online shopping have a significant effect on repurchasing intentions through the mediation effect of shoppers' emotions. Furthermore, Li and Shang (2020) found that perceived information quality and social presence induce customer trust and satisfaction that influence customer engagement behaviors of writing online reviews and purchasing intentions. In the context of SLSPs, viewers' perceptions towards the direct and indirect interactions with different actors (e.g., viewers, streamers, players, and the platform) are strong stimuli that influence viewers' inner affective state (satisfaction) and their behavioral response (virtual gifting).

2.3.2 Value perception of SLSPs and virtual gifting behavior

In the traditional Goods Dominant Logic (GDL), value perception is perceived as ‘the consumer’s overall assessment of the utility of a product based on the perception of what is received and what is given’ (Zeithaml, 1988:14). According to Service Dominant Logic (SDL), customers integrate the service providers’ value propositions (competences and capabilities) to acquire co-created value perceptions (Vargo & Lusch, 2016). In the sports spectatorship, value perception is defined as the perception of value when experiencing a sporting event (Horbel et al., 2016). The theory of value-in-experience (Helkkula et al., 2012) explains the mobile social media consumption experiences and highlights the importance of interaction with multiple actors during the computer-mediated communication processes in social contexts. It is crucial to examine the customers’ perceptions of interactions with actors in the mobile social media consumption process rather than only focusing on the service usage experience. An increasing number of studies have started to use customers’ behavioral big data and the social analytics method to uncover their value perception toward services. For example, Liu et al. (2017) adopted topic analysis to identify the most-discussed brand-related topics of customers perception from 20 brands on Twitter. Our study therefore aims to adopt topic modelling analysis to understand the viewer value perception of interactions with multiple actors when watching sporting events on SLSPs

Customer engagement behavior is a mechanism that allows customers to add value both directly and indirectly to organizations (Pansari & Kumar, 2017). This is in line with the opinion of Kumar et al. (2010) who state that purchasing behavior could be considered as direct contribution, while other non-transactional behaviors such as giving feedback and writing suggestion letters could be seen as indirect contributions. This study focuses on virtual gifting, which reflects the purchasing behavior of viewers.

A positive relationship between customers’ value perceptions and purchase intentions, and between value perception and non-transactional engagement behaviors, has been established by prior studies. For example, LaRose (2001) indicated that the e-commerce environment could stimulate emotional purchases. Guan et al. (2021) found that the social perception with streamers and viewers have a positive effect on viewers' intentions towards virtual gifting behavior in general SLSSs. In this light, it can be expected that the value perception of spectator experiences on SLSPs will encourage viewers to send virtual gifts. Therefore, we propose that:

H1a: Viewer value perception of watching sports events on SLSPs is significantly correlated with the number of gifting.

H1b: Viewer value perception of watching sports events on SLSPs is significantly correlated with the amount of gifting.

2.3.3 The mediation role of Customer satisfaction

Customer satisfaction is conceptualized as consumption-related fulfilment, which is the customer's emotional reaction to the perceived difference between performance appraisal and expectation (Oliver, 1980). Using sentiment analysis, studies have assessed customer satisfaction of services and proved the use of sentiment analysis as an effective tool of customer satisfaction assessment (Gitto & Mancuso, 2017; Lucini et al., 2020). Previous empirical studies have revealed that satisfaction is a result of the customer's value perception towards the provided service performance in various business environments (Xu et al., 2006; Montfort et al., 2000; Moreno et al., 2015). With Web 2.0, customers' perceptions are not only based on information presented on e-commerce websites, but also influenced by interactions with multiple actors on social networks (Carlson et al., 2019). As such, based on a stimuli-organism mechanism, value perception is a robust antecedent of viewer satisfaction on SLSPs. Consequently, we propose:

H2a: Viewer value perception of watching sports events on SLSP is significantly correlated with viewer satisfaction.

Previous studies in social commerce and E-commerce have demonstrated the positive impacts of customer satisfaction on customer engagement behavior (Busalim et al., 2021) and purchasing behavior (Carlson et al., 2019). For example, by collecting data from a social media platforms in China, Carlson et al. (2019) identified that customer satisfaction positively influences purchase behavior on social media. However, in another study on general live streaming services, Clement et al. (2021) found that satisfaction is not associated with virtual gifting intentions. Nevertheless, our focus is on SLSPs where satisfaction is defined as an affective state resulting from an evaluation of the experience of watching sports events. When viewers are satisfied with their experience, they would tend to send virtual gifts. Therefore, we propose:

H3a: Viewer satisfaction is significantly correlated with the number of gifting.

H3b: Viewer satisfaction is significantly correlated with the amount of gifting.

Drawing on the existing literature, we summarized our hypotheses into a conceptual model Fig. 3. We examine how viewer satisfaction influences the relationship between viewer value perception and their engagement behavior as measured by number of gifts sent and amount of gifts are worth.

[Please insert Fig. 3 about here]

3. Research methods

3.1 Data collection

In our study, the log data, the real-time messaging data, and gifting data on the final matchday of the ITTF World Tour Grand Final 2019 (from 12:40 to 21:40 (+8GMT), Dec 16, 2019) from one of most popular streamers' rooms on a major Chinese SLSP were collected. The big data set includes 16,204 real-time messages and 5,540 virtual gifts sent during four matches – the men's doubles (13:00 – 14:00), women's singles (14:10 – 15:10), women's doubles (19:20 – 20:00), and men's singles (20:30 – 21:40).

3.2 Data pre-processing

Firstly, we pre-processed the log data, which included a record of the time and the number of real-time messaging and virtual gifts, as well as the amount of money spent on gifting. These data were transformed to a spreadsheet with intervals of 10 minutes. According to Barbier and Liu (2011), the user-generated content is unstructured, which requires pre-processing and converting to structured data for analysis. This data pre-processing includes four steps. The text is first cleaned by removing numbers, non-Chinese characters, and punctuation, followed by the removal of stopping words. Unlike English, there is no space separator between Chinese characters. In addition, a complete and accurate meaning can only be expressed if two or three Chinese characters are combined (Jia & Chen, 2020). Therefore, in the third step, word segmentation is executed using a word segmentation tool, JiebaR, to split the Chinese characters into meaningful word tokens (Li et al., 2017). To improve the success rate of the domain keyword identification, this research attaches several dictionaries, including professional terms on 'internet service' and 'table tennis' from Sogou.com to JiebaR. Lastly, words with only a single Chinese character (not meaningful) or those with more than four characters (likely to contain more than one meaning) were filtered out.

3.3 Identifying viewer value perception

The latent Dirichlet allocation (LDA) machine learning method is adopted to identify topics that have been discussed the most in real-time messages. LDA could extract latent topics from texts, which reflects a probabilistic distribution of words (Lucini et al., 2020). The R software LDA library toolkit is employed in this study (Li et al., 2017). Topics extracted from the LDA were manually labelled and categorised on value perception according to the combination of human judgement (Guo et al., 2016) with literature on sports marketing and live streaming. To verify the interpretation of topic labels, the original real-time messages that contained these keywords are reviewed to examine whether the original meaning of the message is truly reflected by the labelled topics. Two independent coders were invited to conduct the labelling process independently. Finally, labels of topics are confirmed based on the consensus of both coders.

As a result, 30 topics were extracted using the LDA model. Fig. 4 illustrates an example. Table 2 shows the top 10 out of the 30 topics according to their weights. They reflect which aspects of the table tennis event live streams are most attractive and contribute the most to viewer value perceptions. SDL emphasizes that the value is co-created with actors through interactions, therefore we highlight the actors who are providing value propositions.

[Please insert Fig. 4 about here]
[Please insert Table 2 about here]

From the LDA output, several interesting terms have been observed. These terms were obviously related to the literature of sports marketing, and included words such as ‘membership’, ‘players’, and ‘performance’. In Table 2, there are three topics relevant to sports fans. We first named topic 3 with a weight of 0.59 as ‘Current affairs knowledge’ as these words reflected that the viewers shared and discussed knowledge and information about players’ qualifications for the World Table Tennis Championships, the Table Tennis World Cup, and other Table Tennis mega events. It was a popular discussion topic for viewers, as the results of this ITTF World Tour Grand Final may decide the qualification of players for entering the Olympics Games list. Nevertheless, online sport viewers, like other sports customers, may co-destroy value through their behaviors. In Table 2, topic 10 (weight 0.5) was named ‘Dysfunctional behavior’ based on the words ‘internet trolls’, ‘moral quality’, and ‘verbal aggression’, as they have appeared in the value co-destruction literature (Giulianotti, 1999;

Stieler et al., 2014). These words reflect that the viewers care about another fan’s behavior and seek a healthy spectating environment. Furthermore, as observed in Table 2, topic 6 (weight 0.54) was named ‘Fan identification’ based on the words ‘forever’, ‘support’, and ‘feel proud though defeated’. The viewers expressed that they would support the player forever although he/she lost the match, and that they feel proud of the player for fighting hard despite his/her injury. In addition, the sports player is a particularly important actor contributing to viewer value perception. In this study, it is worth noting that the topics of ‘Mental toughness’ (weighted 0.55), ‘Strategic performance’ (weighted 0.51), and ‘Technique performance’ (weighted 0.5) have been identified based on the extracted performance-related topics. Moreover, with a similar weight of the player-related topics, the ‘Opposing teams’ are identified as naturally contributing to the viewers’ experience of the game. In previous studies, the opposing teams would often appear in value co-destruction literature (Giulianotti, 1999). Sports fans with high team identification are prone to be affected by the performance of the opposing team. However, as shown in Table 2, the opposing team-related topics identified in this study are positive topics, such as ‘beautiful girl’, ‘reserve players’, ‘cute’, and ‘relax’. This result indicates that the table tennis Chinese fans expect to see rivals from other countries coming to challenge China’s dominance in the table tennis world. This could then provide a better viewing experience for viewers, with unpredictable results. The next important category is the ‘Prize distribution’ (weighted 0.47), which is relevant to the sports event organization. Topics such as ‘prize’, ‘dollar’, ‘less’, and ‘distribution’ were extracted from our real-time message corpus. For instance, customers compared the amount of money the players were awarded between table tennis and other sports and voiced complaints about the table tennis players earning less money. These viewers were expressing their thoughts on the pay gap between sports, which indicates that the sport fans are interested in the prize distribution. The LDA analysis also reveals two other categories (both weighted 0.43), namely ‘Information quality' (contributed by the platform) and 'Streamer endorsement' (related to streamers), which are relatively new to the sports marketing research. With the increasing use of smartphones and Internet technologies, SLSPs have changed the way the viewers capture the essence of sporting events. In this study, the SLSP added new functions of the 360-degree view, the multi-screen display, and virtual reality environment. These efforts are an attempt to enable viewers to enjoy the sporting event from every conceivable angle (e.g., coach/player/training venue angle). Accordingly, information quality emerged as a crucial topic among the live sport streamer viewers, demonstrating the significance of perceived quality provided by the live streaming platform in the overall viewing experience. For example, viewers mentioned 'perspective', 'coach', 'screen', 'surprise', and 'switch' in real-time messaging when expressing their opinions and experiences with the new functions. Streamer endorsement is the other topic category that emerged from the analysis. The endorsement involves three characteristics, which are attractiveness, trustworthiness, and expertise (Ohanian, 1991). In SLSPs, streamers interact with viewers directly by commentating on matches, addressing viewers' questions by using their voice, visible physical behavior, and sharing their knowledge of the sports match (Kim & Kim, 2020). When a streamer reaches the level of attracting a certain number of viewers, s/he becomes well known and hence can have the same kind of endorsement effects as other celebrities (Chen & Lin, 2018). In the results of the LDA analysis, the terms 'handsome' and 'streamer' have been singled out as confirmation of the above findings. The streamers on SLSPs plays the role of a separate commentator for the contents of the competitive matches. Therefore, knowledge of the sport and framing skill (Parker & Fink, 2008) are rather crucial factors for streamers to give viewers meaningful insights about the game. Clearly, our research supports this point of view from 'commentary' and 'brilliant'. Meanwhile, the words 'racket case', 'working hard', 'purchase', and 'thanks' also support the assertion that viewers were influenced by the streamers. This result demonstrates that the streamer is one of the most important elements that can affect viewers' experience. The findings from the above analysis yield insights into the viewer value perceptions of the viewing experience on SLSPs.

By combining with time-series analysis and words frequency analysis, the most frequently mentioned words in every 10-minute interval are extracted. The word cloud in Fig. 5 (Panel A) illustrates the changes of the discussed topics at different peak times. The value perception rate in each 10-minute interval have been calculated based on equations (1) and (2) to test the hypotheses later. The value perception rate reflects the level of these extracted value perceptions every 10 minutes. Topic weight (TW_i) is the weight for each of the 10 topics, where the value perception rate (VP_{ij}) is the sum of the topic weights per 10-minute interval multiplied by the frequency of the topic-related words.

$$TW_i = \frac{\lambda_i}{\sum \lambda_i} \tag{1}$$

$$VP_{ij} = \sum TW_{ij} N_{ij} \tag{2}$$

[Please insert Fig. 5 about here]

3.4 Identifying viewer satisfaction

The sentiment analysis is calculated by the HowNet Lexicon software (Xianghua et al., 2013) to investigate the viewer satisfaction. Sentiment analysis is a method that is used to detect subjective information automatically from textual data (Xianghua et al., 2013; Jia & Chen, 2020). To conduct the sentiment analysis, we first annotated the texts by scoring adjectives with known orientation scores (positive emotional words +1, negative emotional words -1). We then calculated the overall sentence score by considering whether there is an adverb (scores +3, +2, or +1) and a negative evaluation word (scores -1) in front of the emotional words. This is because the negative words can affect the emotional polarity in Chinese expression, such as ‘no’, ‘do not’, and so on, while adverbs can strengthen or weaken the degree of emotion, such as ‘very’, ‘special’, and so on (Jia & Chen, 2020). Finally, the overall sentiment was calculated by subtracting the negative sentiment score from the positive sentiment score. In this research, we used the R programming language to conduct the analysis. To clarify how to relate the sentiment score to the real-time comments, we chose one simple example from our message database:

The quality of this shot is very good. [sentiment scale result: 3]

In this example, the score for each key word is: [3] for ‘very’ and [1] for ‘good’. Therefore, the overall result for the sentence is 3, calculated from 1*3.

From the results of the HowNet analysis, the overall average sentiment score of the perception dataset is 0.33, which indicates a moderate positive attitude towards the viewing experience of the sporting event on SLSPs. In addition, according to the results, the numbers for positive, neutral, and negative messages are 4856, 9717, and 1632, respectively. This indicates that there are more messages expressing positive feelings than negative feelings. The word cloud analysis was then conducted to visualize the most frequently mentioned categories for extremely satisfied experiences and extremely dissatisfied experiences, as shown in Fig. 6. As the database is in Chinese, the extracted words were translated into English before generating the English version of words clouds. The results indicate that the players’ performances, including mental toughness, strategic performance, and technique performance, are frequently mentioned in both the positive and negative reviews. However, many positive words that have been mentioned with ‘Sport fan identification’ and ‘Opposing team performance’ reflect the extremely satisfied experience, while ‘Dysfunctional behaviors’ is identified as the trigger for an extremely dissatisfied experience.

[Please insert Fig. 6 about here]

Same as with identifying the viewer value perception, we also combined time series analysis and sentiment analysis to explore the viewer sentiment over time when viewing the sports streams on SLSPs. Due to a long break between the afternoon matches and evening matches which lack real-time messages for sentiment analysis, we calculated the sentiment of the real-time messages based on 10-minute intervals from 13:00 to 15:20 and from 19:20 to 21:40. Fig. 5 (Panel B) illustrates the changes of sentiments, which shows that the positive sentiment has a downward trend while the negative sentiment has an upward trend from 13:00 to 15:20. From 19:20 to 21:40, the positive sentiment has an upward trend while the negative sentiment has a downward trend.

4. Results of hypothesis testing

4.1 Descriptive statistics

Fig. 5 (Panel C) shows the number and the amount of gifting for each 10-minute period. The amounts of gifting represent how much money was spent by viewers to purchase and send the virtual gifts.

In total, there are thirty 10-minute intervals of value perception, sentiment, gifting number, and gifting amount data which were used to test the proposed hypotheses. The descriptive statistics and the correlation analysis are detailed in Table 3. The result of the correlation analysis shows that all the variables are highly related to each other.

[Please insert Table 3 about here]

4.2 Structural equation modelling analysis

The structural model is tested based on path coefficients and the results of all hypotheses are summarized in Table 4 and Fig. 7. According to path coefficients, value perception (β 0.31, $p < 0.01$) exerted directly and significantly positive impacts on number of gifts, but no significant effect on gifting amount, thus supporting H1a but rejecting H1a. As hypothesized, there is a relationship between value perception and satisfaction. Specifically, value perception significantly affects satisfaction (β 0.69, $p < 0.001$), supporting H2. Additionally, satisfaction positively influences gifting number (β 0.69, $p < 0.001$), and gifting amount (β 0.44, $p < 0.05$), thus H3a and H3b were supported. According to the results, the explained variances (R^2) of 0.48 for satisfaction, 0.85 for gifting number, and 0.43 for gifting amount demonstrate a satisfactory level of predictive power.

[Please insert Table 4 about here]

[Please insert Fig. 7 about here]

Although there was no direct effect of value perception on gifting amount, there may be some indirect effects (Hayes, 2009). Therefore, we further tested the indirect effects to explore potentially important mechanisms whereby value perception may impact customer engagement (gifting number and gifting amount). As recommended by Nitzl et al. (2016) conducted mediation analysis to test the role of satisfaction in mediating the effect of value perception on customer engagement. At 95% bias-corrected confidence interval based on 2,000 bootstrap samples, the results of indirect/mediating effects are displayed in Table 4.

When satisfaction was introduced into the model, there was no significant direct effect of value perception on gifting amount (see Table 4). Nevertheless, value perception had a significant indirect effect on gifting amount through satisfaction (CI 0.306 to 0.843). Specifically, value perception indirectly impacts customer engagement of gifting amount through satisfaction. Therefore, value perception fully mediates the effects of value perception on customer engagement of gifting amount. As for gifting number, both the direct and indirect effects were both significant. Thus, satisfaction partially mediated the effects of value perception on consumer engagement (CI 0.055 to 0.796). Overall, there is a significant total effect of value perception a on gifting number (β 0.78, $p < 0.01$) and gifting amount (β 0.58, $p < 0.01$).

5. Conclusion and Discussion

This study relies on user-generated data from a major Chinese SLSP to establish the relationship between value perception, satisfaction, and gifting behavior. The construct of value perception and satisfaction are calculated based on a machine learning approach. Firstly, topic modelling analysis was adopted for exploring the real-time message content. The result revealed the natural and hidden topics within the text. Such information acts as a source for understanding the perceptions of viewing sporting events in the context of SLSPs. Based on word frequency and time series analysis, value perception rates over thirty 10-minute periods are calculated. After that, the results of the sentiment analysis presented the viewers' overall experiences and sentiment over time to reflect the change of viewer satisfaction levels. Building on constructs developed from actual data in live streaming services to uncover customer engagement behavior, our results confirmed the positive association between viewer value perception, satisfaction, and gifting behavior. To the best of our knowledge, this is the first attempt to use machine learning approaches to develop a construct for building the conceptual model.

Based on the S-O-R framework, the viewer value perception can affect the viewer satisfaction with their watching experience, which in turn determine their gifting behavior. More specifically, satisfaction fully mediates the effect of value perception on gifting amount while partially mediating the influence of value perception on gifting number. In contrast to previous works, which found no effect of satisfaction on gifting intention (Clement et al., 2021), we found that viewers would like to send virtual gifts, especially those with higher value, when they are satisfied with watching sports events on SLSPs. The virtual gifts with lower value are serve more as 'emojis' for viewers to express their emotions.

5.1 Theoretical implications

As a newly emerged type of synchronous social media platforms, SLSSs have attracted increasing research attention targeted at exploring users' value perceptions and engagement behavior. The dynamics in the effects of value perception on engagement or purchase intention are explored well in the existing literature. However, most studies that focus on measuring users' behavioral intentions and value perceptions do so through interviews and surveys rather than using actual behavioral data (Hedlund, 2014; Qian et al., 2020). Within the era of Web 2.0, applying big data of SLSPs for building and analyzing conceptual models offers significant potential for marketing scholars who seek to understand the actual viewer engagement and experience. Previous studies have also explored the impact of consumers engagement behavior (likes, visit, chat, and exposure time) and emotion on purchase intent or gifting behavior. However, it is essential to examine how the viewer value perception towards the viewing experience works to define the actual gifting behavior in sport live streaming platforms, especially when satisfaction is considered. In this study, we identified a vital proxy of topic rate and sentiment, which represents the variable of value perception and satisfaction. Although these proxies are typically collected from surveys and interviews in the existing literature, the actual data analyzed in this study could avoid the problem of bias and sample size. Hence, by combining machine learning techniques and SEM, our study makes an early attempt to use actual behavioral data to explore the mediation role of satisfaction between value perception and gifting behavior on SLSPs.

From the topic modelling approach, this study identified topics that were discussed by and shared among viewers the most during the live streams. In line with the present literature of sports marketing and value co-creation, our findings also indicate that the streamer and other viewers directly contribute to viewer value perceptions while the players, teams, and the event organization indirectly contribute to viewer value perceptions of SLSPs. Therefore, these findings help to extended theoretically the boundary of the value co-creation studies into the context of SLSPs. By applying sentiment analysis, this study tested the overall viewer sentiment over time and showed the trend of the positive sentiment and negative sentiment. This word cloud analysis illustrated that the players' performance is a critical factor influencing the viewer experience. Moreover, other viewers' dysfunctional behaviors can lead to negative viewing experiences. Therefore, sports marketers should be more vigilant in moderating the viewing environment.

5.2 Managerial implications

In general, there are several important implications of this research for management. The results of this study can be used by marketers in the sports live streaming field to set up better marketing strategies.

Firstly, the topic modelling results offer a guideline for SLSPs marketers on how to improve their engagement with viewers. These topics provide important information for SLSPs marketers because what customers discuss on SLSPs during the live streaming reflects their value perceptions and set the grounds for their future engagement. As mentioned above, SLSPs rely heavily on sporting events copyright, which can enable SLSPs to win a huge viewer base. However, the platform would experience a substantial reduction in viewers after the event finishes. Therefore, the viewers' attention beyond the game time is important. The topics identified in this study can be used as a reference for SLSPs to understand what is more meaningful for viewers to share and chat about after the game. More specifically, since companies are aware that these topics can trigger great discussions, they should select these topics and set up topic-specific discussion communities on the homepage. Even after the match finishes, these discussions will be continued as a way for viewers to digest their excitement and exchange knowledge. The SLSPs, in turn, can retain viewers and increase the number of daily active users (DAU).

Secondly, findings of the overall sentiment analysis have clear implications for marketers to select the materials for rebroadcasting and generating short videos for attracting viewers during the off-season. Furthermore, SLSPs should set up the discussion topics according to positive words to sustain a high level of satisfaction for the viewers' viewing experience. Meanwhile, efforts should be made to manage customers' negative perceptions, which are indicative of an extremely unsatisfactory experience.

Lastly, from the results of SEM, we argue that SLSPs managers should consider the value co-created by different actors for viewers and facilitate viewers to share satisfied watching experiences for subsequent gifting behaviors.

6. Limitations and future research

This study has limitations which indicate possible future research. First, the data were based on four matches on a matchday of a table tennis event, and we acknowledge that these viewing behaviors may be different from viewers in a different sport, such as football and basketball, which have a longer and more continuous game time for each match. Further, this study only focusses on gifting behavior, which is one of the profit models. We suggest that similar studies can be conducted to explore social live streaming shopping behavior, which is a novel profit model on SLSPs. As customer engagement in live streaming services tend to become a trading research area, further research could adopt actual behavioral data, and combine both big data analytics and structural equation modelling to explore the viewer behavior.

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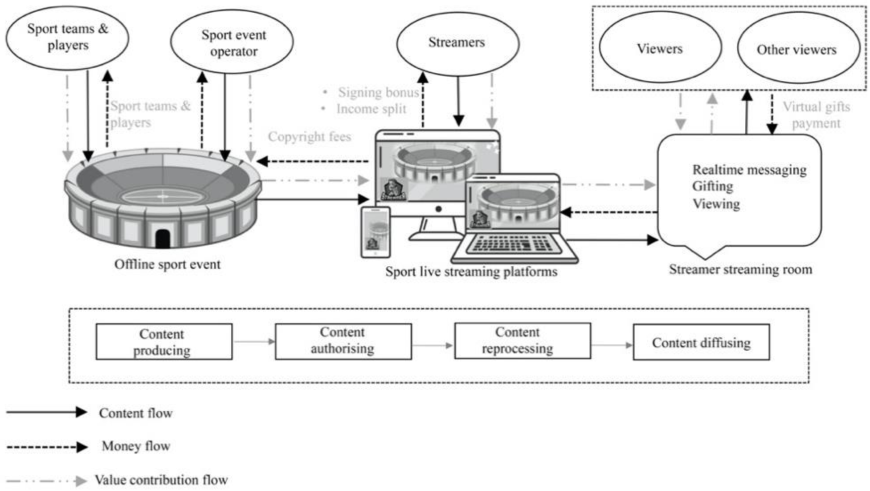


Fig. 1. The operating mechanism of SLSPs.

Fig. 2. China Sport interface when watching a stream.

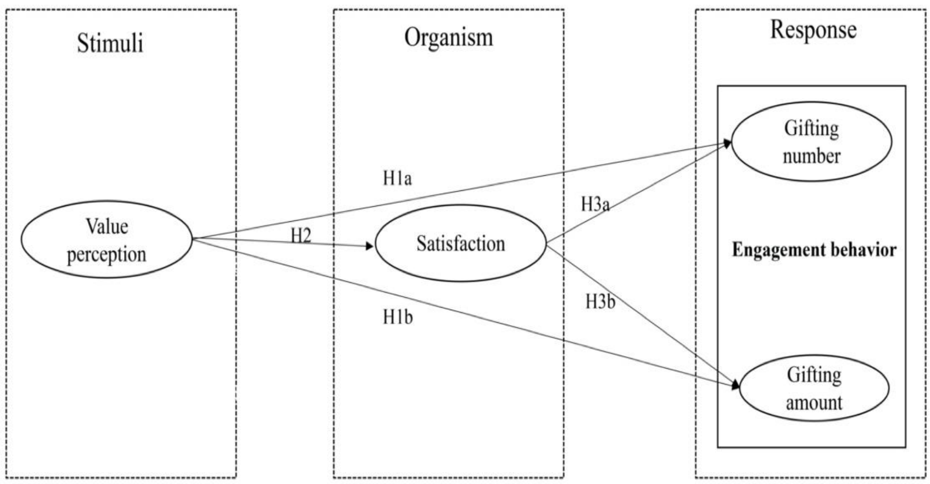


Fig. 3. Map of hypothesis.

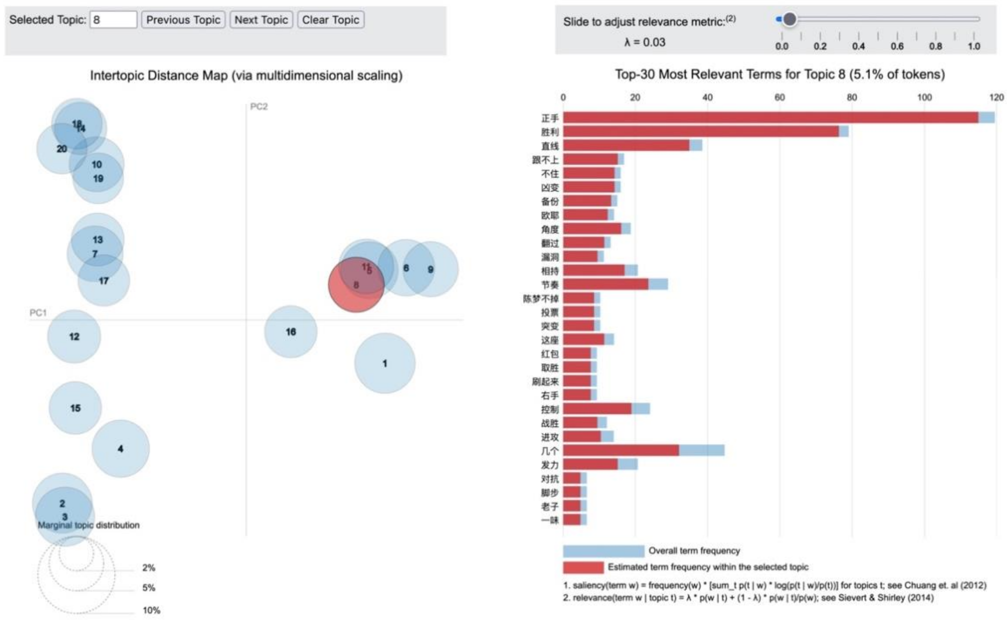
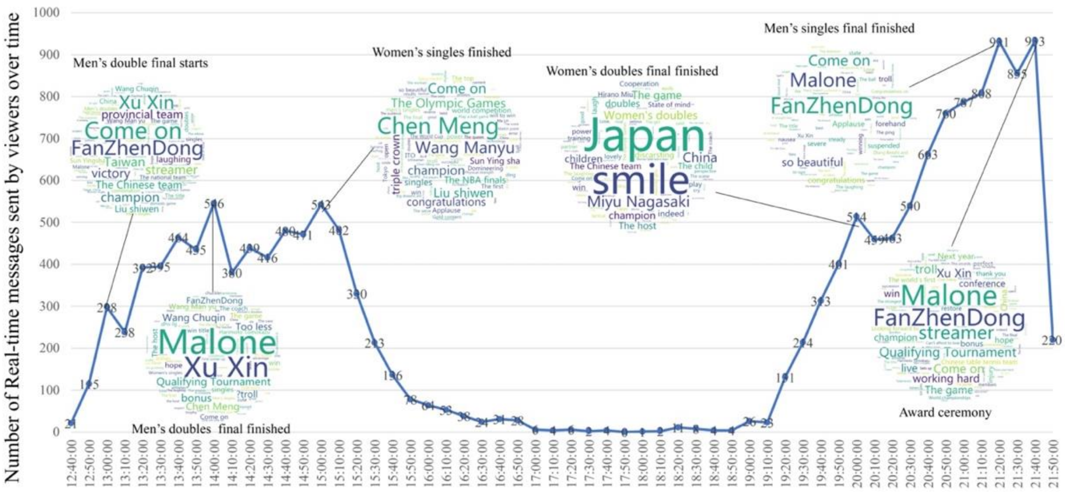
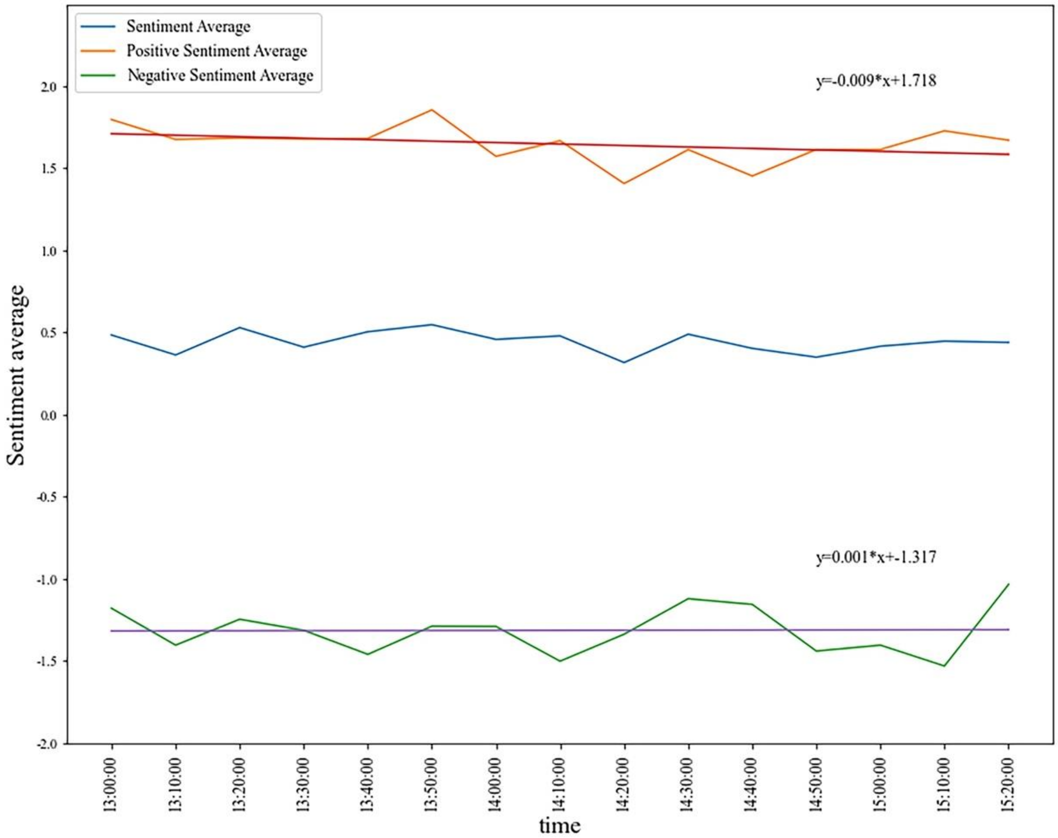


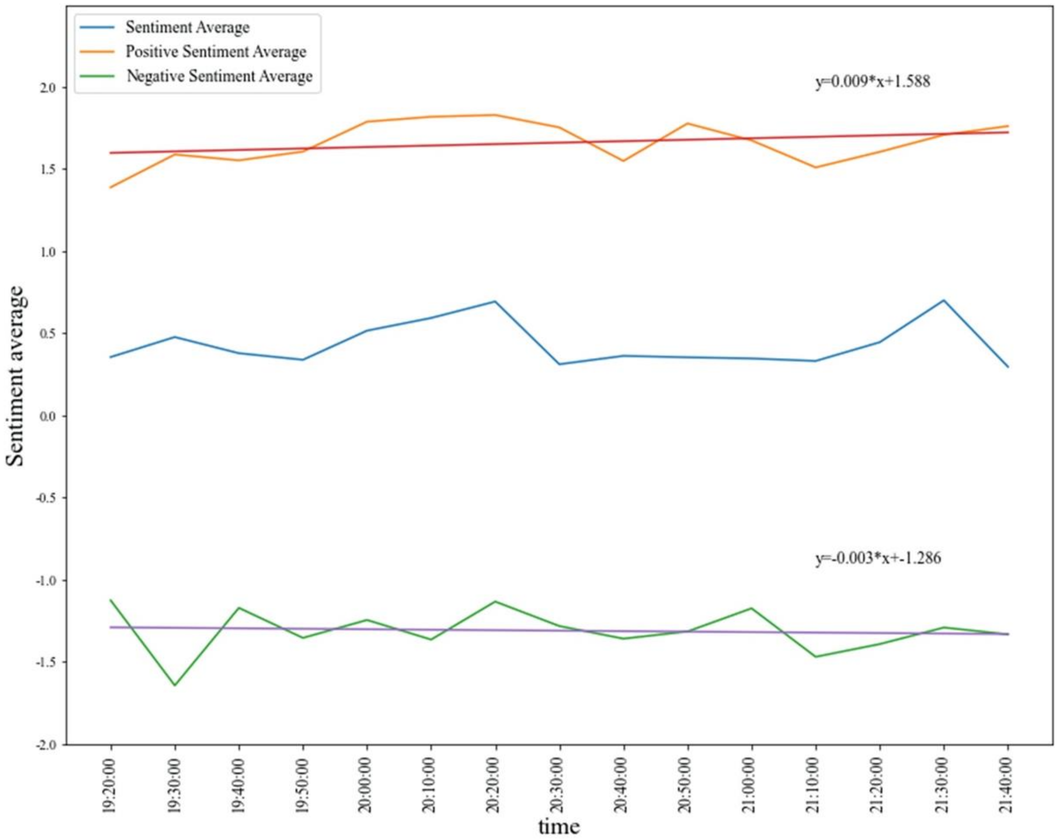
Fig. 4. An example of the results of an LDA analysis.



Panel A: The change of real-time messages and word clouds.



Panel B – 1: The change of sentiment from 13:00 to15:20.



Panel B – 2: The change of sentiment from 19:20 to 21:40.

Panel C: The change of virtual gifting (number and amount).

Fig. 5. Results of the time series analysis.

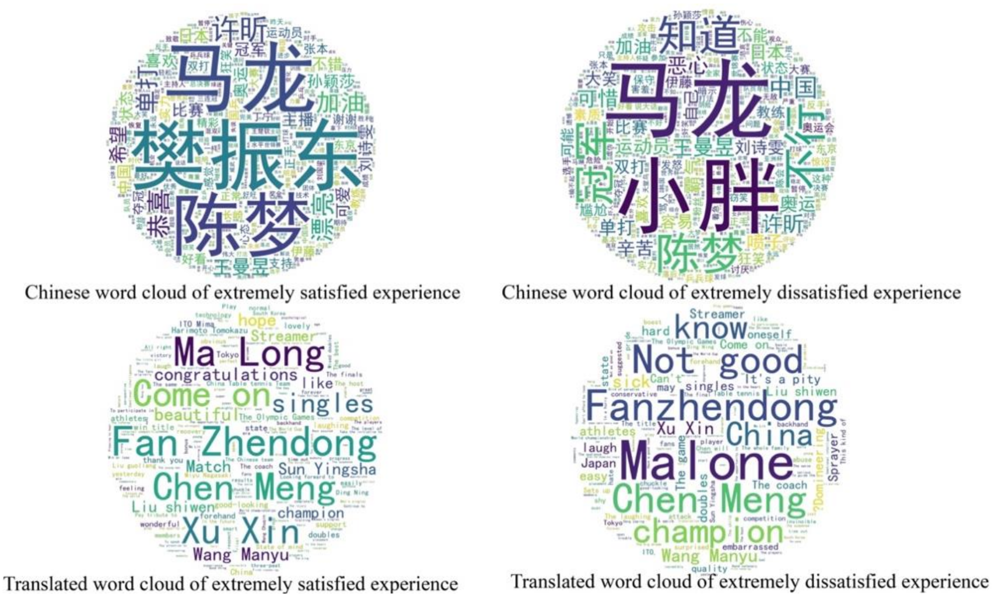
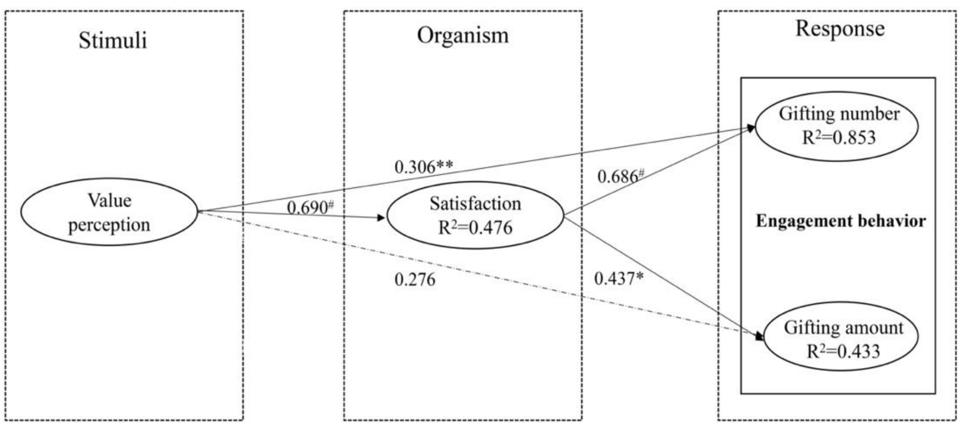


Fig. 6. Word clouds of the positive and negative messages



*p< .05, **p< .01. #p< .001.

Fig. 7. Amos results of structural model

Table 1
Table of reviewed literature

Author(s) (Year)	Type	Methodology/ data/samples	Key finding(s)	Comparison with current study
(1) Kim & Kim (2020)	E-sport platform	Survey (399 YouTube Live e-sport viewers)	• The study found that flow experience is significantly affected by achievement, drama, and player skills. The subjective well-being is significantly impacted by achievement, friendship, and social dimensions. There are significant correlations between the flow experience, subjective well-being, behavioral intentions, and game loyalty.	(1)-(4) These four studies collected survey data from E-sports platforms. They focus on how different variables impact the viewers' engagement behavioral intentions when watching sports game livestreams. The current study collected actual behavior data and used machine learning and exploratory analysis to find out whether topics, sentiment, and number of people can influence gifting behaviors.
(2) Hilvert-Bruce et al. (2018),	E-sport platform	Survey (2227 Twitch users)	• This study identified that social interaction, sense of community, meeting new people, entertainment, information seeking, and a lack of external support in real life are related to live stream engagement.	
(3) Jang et al. (2020)	E-sport platform	Survey (598 E-sport players)	• This study found that the intention of esports content live streaming consumption played a full mediation role in the relationship between esports recreational gameplay behavior and the intention of esports event broadcast consumption.	
(4) Qian et al. (2020)	E-sport platform	Survey (1309 viewers of social live streaming in China)	• This study indicated that commitment mediates between push factors and watching behaviors, between push factors and playing behaviors, between pull factors and WOM intentions, and between pull factors and watching behaviors.	
(5) Kim and Kim (2020)	Sports event on E-sport and general social media platform	Survey (231 SLSS users)	• This study found that four types of gratification expectations positively influenced the users' flow states. Among users who identify with their preferred teams to a great extent, affective gratification exerted the greater impact on the flow, predicting satisfaction with SLSSs, which in turn enhanced the social wellbeing of viewers and ease their feelings of loneliness.	(5)-(6) These two studies investigate study the sport event live streaming services, which is the same as this current research. They use survey data to understand the viewers' behavioral intentions and psychological results, while this current study collected actual behavioral data and used big data analysis to find out whether topics, sentiment, and number of people can
(6) Qian (2021)	Sports event on E-sport platform	Survey (524 TNF viewers on Twitch)	• This study found that continuous watching intentions is positively impacted by co-streaming fit factors and virtual interactions. Co-streaming fit was found to mediate the effects of co-streamer expertise and viewer identification on behavioral proclivities.	

				influence sports viewers' gifting behaviors.
(7) Guo et al. (2021)	S-commerce	Survey (422 Taobao Live customers）	• This study found that trust in broadcasters has a positive effect on trust in products and community members, which positively influences trust in products. Additionally, swift guanxi has a fully mediating effect on the relationship between customers' trust in broadcasters and customer engagement.	(7)-(9) These three studies still use survey data to measure the effects of trust and social factors on customers' behavioral intentions. This current study adopted actual customer engagement behavioral data to predict viewers' gifting behaviors.
(8) Wongkitrungrueng & Assarut, 2018;	S-commerce	Survey (246 Facebook users in Tailand)	• This study found that symbolic value has a direct and indirect influence through trust in sellers on customer engagement, while utilitarian and hedonic values are shown to affect customer engagement indirectly through customer trust in products and trust in sellers sequentially.	
(9) Li et al. (2021)	S-commerce	Survey (425 Taobao Live users in China)	• This study found that ethnical factors (synchronicity and vicarious expression) and social factors (interaction and identification) positively affect emotional attachment to streamers and platform attachment, respectively, which in turn improves the user stickiness.	
(10) Hou et al. (2019)	General SLSSs & Topic-specific SLSS	Mix-method (interview and Survey of 350 responses.)	• This study found that continuous watching intention is influenced by interactivity and humor appeal while consumption intention is impacted by social status display and sex appeal, but this varies across different live streaming types.	(10)-(18) These studies also use survey data to measure general SLSSs customers behavioral intentions, including continuously watching intentions, consumption intentions, and usage intentions. This current study adopted actual customer engagement behavioral data to predict viewers' gifting behaviors on sports live streaming services.
(11) Hsu & Lin (2021)	General SLSSs	Survey data collected from 304 general SLSS users	• This study confirmed that gratifications such as entertainment, informativeness, and sociability were all positively related to satisfaction. The authors find that flow mediates the impact of interactivity and telepresence on satisfaction. Notably, sociability gratification and satisfaction had a significant impact on a user's intention to continue to use livestreaming services and accounted for 77% of the variance.	
(12) Chen & Lin, 2018)	General SLSSs	Survey (313 Taiwanese)	• This study indicated that flow, entertainment, social interaction, and endorsement have a positive relationship with attitude, perceived value, and watching intention.	

(13) Scheibe et al. (2016)	General SLSSs	Survey (123 YouNow users) & observation	• This study revealed that information behavior on YouNow shows some similarities to information behavior on asynchronous social media. YouNow users like to watch streams, to chat while watching, and to reward performers by using emoticons.
(14) Wan & Wu (2020).	General SLSSs	Survey (244 viewers of social live streaming in China)	• This study confirmed that viewers' enjoyment with broadcasters was positively associated with their parasocial relationship with the broadcasters, which in turn led to increased loneliness and addiction among the viewers. Viewers' perceptions of loneliness were also a direct factor that influenced their addictive media usage.
(15) Chen, et al. (2020)	General SLSSs	Survey (420 live streaming users)	• This study developed and validated a 35-item online live streaming perceived servicescape scale with eight dimensions. The results of the empirical model showed that OLSPS is positively related to the audiences' cognition and behavioral intention. Moreover, parasocial interaction experience have a positive moderation effect on channel trust.
(16) Guan et al., (2021)	General SLSSs	Survey (461 valid live streaming users)	• This study also reveals how such social perceptions can be shaped by the contextual setting consisting of the IT-related factors of live streaming (i.e., responsiveness, two-way communication, social presence, and self-presentation) and the cultural characteristics of China (i.e., social orientation and harmony).
(17) Li et al. (2018)	General SLSSs	Survey (609 people valid live streaming users)	• This study found that flow mediates the effects of contextual factors (interactivity and social presence) and personal factors (trait curiosity and social media dependence) on consumption intention. It reveals gender differences in flow's influence on the consumption intention of virtual gifts.

(18) Su et al. (2020)	General SLSSs	Survey (552 Chinese live streaming platforms users)	• This study confirmed that online gift visibility of live-stream marketing can be used as a sustainable strategy to stimulate customers' purchase intentions. Social presence mediates the relationship between the gift's visibility and green purchases. Self-monitoring personality moderates the relationships among the online visibility of virtual gifts, social presence, and green purchase intention.	
(19) Clement et al. (2021)	S-commerce	Data mining and observation (1726 live and public data from Taobao and JD)	• This study suggested likes, chats, visits, and exposure time in social commerce have positive impacts on transactional (purchase) and non-transactional (followership) intention.	(19)-(20) Same as the current study, these two studies creatively adopted actual customer engagement behavioral data to explore s-commerce and general SLSSs live streaming engagement behaviors. They tested the influence of likes, chats, visits, exposure time, and emotions on intended purchasing and tips. This current study explores how topics, sentiment, and number of people can influence gifting behaviors (number of gifts and number of gifts)
(20) Lin et al. (2021)	General SLSSs	Data mining for 120 minutes of the sessions (data provided by a popular live streaming platform in China)	• This study found that the broadcasters and viewers influence each other in terms of emotions. The broadcaster's emotional response to viewer emotion, compared with viewers' responses to broadcaster emotion, is larger in terms of both immediate effects and longer-lasting effects. The broadcaster emotion helps attract viewer tips and stimulate viewer liking and chatting (measures related to viewer attitude).	

Table 2
The result of LDA analysis.

No.	Topic no.	Weight	Keywords	Topics	Actor
1	3	0.59	Champion；World tour final；mega event；World Cup；World championship; next year; attendance; qualification; score；result; places	Current affair knowledge	Fans
2	4	0.55	Stable; Manyu Wang; confidence; psychology; performance on-spot; determination; strength; invincible opponent; non-match time	Mental toughness	Players
3	6	0.54	Forever; support; powerful; well done; feel proud through defeated; captain; pity; try your best; good thing; injury	Sport fan identification	Fans
4	7	0.52	Japan; young girl; beautiful girl; reserve players; women's doubles; cute; group; relax; Chinese; pressure	Opposing team performance	Teams
5	8	0.51	Forehand; down the line; win; pace; control; attack; angle; shortcoming; Rally; change；	Strategic performance	Player
6	10	0.5	Internet trolls; moral quality; verbal aggression; on-stadium; spectator; comments; curse; defame; respect; fans; players	Dysfunctional behavior	Fans
7	11	0.5	Quality; sweep; change; single shot; brute force; skill performance; professional; confrontation; peak form; one-sided game	Technique performance	Players
8	12	0.47	Prize; Dollar; less; external match; allocation; singles；doubles; champion; endorsement; male and Female; top four	Prize distribution	Event Organization
9	18	0.43	Training; coach; perspective; level; shot; computer; interpreter; image; screen; surprise; switch	Information quality	Platform
10	19	0.43	Membership; handsome; streamer; commentary, racket case; working hard; purchase; brilliant; lottery; thanks	Streamer contribution	Streamers

Table 3
The result of descriptive and correlation analysis.

Variables	Mean	SD	Min	Max	1	2	3	4
1. Value Perception	55.46	18.12	23.71	100.08	1.00			
2. Satisfaction	213.89	105.99	46.50	598.50	0.690#	1.00		
3. Gifting number	175.03	444.23	1.00	1919	0.779#	0.897#	1.00	
4. Gifting amount	4112.41	7929.98	5.00	41485.0	0.577**	0.627#	0.667#	1.00

Significance level *p < .05, **p < .01, #p < .001

Table 4
The result of hypothesis testing.

	Coefficient	Standard Deviation	T statistics	R^2	Hypothesis Result
Value perception → Gifting number	0.306	0.773	5.215^{**}	0.853	H1a: Supported
Value perception → Gifting amount	0.276	0.002	7.111	0.433	H1a: Not supported

Value perception → Satisfaction	0.690	0.004	2.301$^{\#}$	0.476	H2: Supported
Satisfaction → Gifting number	0.686	0.011	3.167$^{\#}$	0.853	H3a: Supported
Satisfaction → Gifting amount	0.437	0.026	1.454*	0.433	H3b: Supported
	Total effects			**Indirect effects**	
	Coefficient	Bootstrap 95%CI		Coefficient	Bootstrap 95%CI
VP→GN	0.78**	[0.529:0.993]	PV→S→GN	0.473**	[0.306:0.843]
VP→GA	0.58**	[0.251:0.793]	PV→S→GN	0.301*	[0.055:0.796]

Significance level *p < .05, **p < .01, $^{\#}$p < .001; Notes: VP = Value Perception, GN = Gifting Number, S = Satisfaction, GA = Gifting Amount.