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# The Social Impact from Danmu—Insights from Esports Online Videos

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**Abstract:** An emerging online social interaction feature, Danmu, which overlays viewer comments on online videos, has become increasingly popular on video-sharing platforms. Danmu comments may have a social impact on potential viewers' behavior and thus have important implications for online video consumption. Drawing on Social Impact Theory, this paper explores how Danmu comments affect both viewers' viewing behavior and engagement behavior in online esports videos. Our results reveal that Danmu comments consistently improved the number of views of esports videos. Danmu comments also positively influenced the level of viewer engagement, but the size of this impact was smaller than that on viewers' viewing behavior. Moreover, Danmu comments played a greater role in viewers' viewing behavior of full-length competitive esports matches than that of video clips. Finally, Danmu comments' differential impacts on viewers' engagement behavior between full-length matches and video clips vary by esports games.

**Keywords:** Danmu; social impact; esports; online video; engagement; social interaction

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## 1. Introduction

Online media content are accessible on a variety of electronic devices with internet connectivity. Consuming media content has become one of the most popular internet activities of late: according to a Nielsen survey, 80% of the general U.S. population watched video content online in 2018 [1]; by the end of 2020, 944 million Chinese users watched online video content, accounting for 95.4% of all Chinese internet users [2]. The digital consumption of media content has become a new trend of electronic commerce.

The expansion of online video consumption has been accompanied by innovative elements intended to attract viewers and to enhance the viewer experience. Features conducive to online social interaction have seen particularly rapid advances. For instance, YouTube Live and MLB TV broadcast sport games online offer viewers a chat function, so fans can cheer for their favorite teams and players or communicate with other viewers in real time [3]. A more recent interactive feature, Danmu (in Chinese, or Danmaku in Japanese, translated as "bullet screen" or "barrage" in English), has proliferated on video-sharing platforms in Asia and particularly in China [4]. Danmu displays moving real-time viewer comments on the screen rather than beside the video (see Figure 1). It provides a novel way for viewers to express their reactions, emotions, and opinions about video content in real time. Danmu essentially creates a co-viewing experience in which viewers feel as if they are watching alongside their peers [5]. Viewers can use Danmu to participate in conversations, share knowledge, earn recognition, and develop a sense of companionship [6,7]. Danmu thus embodies a virtual version of the interaction common in in-person spectatorship [4,8]. Compared with live chats and chat rooms where viewer interactions typically occur while synchronously watching live videos, Danmu collects viewers' spontaneous reactions to specific video content even if they watch the video at different times, and displays them on the screen synchronized to the video timeline. Danmu thus extends the co-viewing atmosphere to an asynchronous environment.


**Figure 1.** An example of Danmu (Danmu are real-time viewer comments displayed on the screen) on Bilibili.com (accessed on 22 May 2021).

Danmu was created in 2006 by Niconico, a Japanese video-sharing service. It gained popularity in the subculture of animation, comics, and games (ACG), where consumers of these media content often have shared interests and seek community through Danmu interactions. Danmu was first introduced to China by AcFun (acfun.cn) on 2008, and was subsequently adopted by Bilibili.com, where its popularity exploded. To date, Danmu is widely employed by video-sharing platforms in China, and it is available for media content beyond ACG, including TV series, movies, and sport competitions. Viewers actively participate in sending Danmu comments. Bilibili, for example, recorded more than 10 billion Danmu comments posted by over 60 million users as of December 2021 [9]. Meanwhile, few western media platforms have introduced Danmu as a social interaction feature. Unlike the Chinese and Japanese, which use a single or a small number of characters to represent a word, other languages such as English and German are alphabet-based, with longer words and sentences. Since Danmu flies through comments on the screen, concise writings are easier to read and are less likely to obscure other viewers' line of sight. However, with the increasing use of emotion icons in internet conversations, such as smileys, pictograms, and emojis, comments in English and other alphabet-based languages are substantially shortened, which could make Danmu an appealing interaction tool.

In light of the video-sharing platforms' ongoing evolution and emerging social interaction features, it is critical to assess the impact of these online interaction tools on viewer behavior. Such an understanding would present valuable insights for platforms to make strategic decisions in order to attract and retain viewers. Recent studies in marketing and information systems have acknowledged the importance of real-time interactive features for online video-sharing platforms [10,11]. As a novel and emerging feature, Danmu has also garnered increased academic attention [12,13]. Viewers' expression of opinions via comments could create a social impact [14] that leads to changes in other users' behavior [15]. Drawing on Social Impact Theory [16], this paper investigates the impact of Danmu comments on the viewing behavior and engagement behavior of online viewers. Using two popular esports games, League of Legends and Overwatch, as our research subjects, we sourced data from Bilibili. We performed two sets of analyses to draw conclusions. First, we examined Danmu comments' influences on the behavior of online viewers of full-length professional esports matches. Second, we further scrutinized the effect of Danmu by comparing full-length matches with esports video clips. In both analyses, we applied a two-stage least squares regression model with instrumental variables [17–19] to alleviate endogeneity concerns. Our study thus aims to provide a more holistic understanding of Danmu's effectiveness and to offer important practical implications to video-sharing platforms whose profits and sustainable development rely heavily on viewership and viewer experience.

## 2. Literature Review

### 2.1. Social Impact Theory

According to Social Impact Theory [16], people (the target)'s behavior, feelings, and thoughts can be influenced by others' (influencing group) presence or actions. The impact results from three social forces: strength, number, and immediacy. Strength considers how important the influencing group is to the target. Immediacy refers to the closeness between the target and the influencing group. Number refers to the size of the influencing group.

A stream of research in marketing and information systems focuses on the effect of number, i.e., the size of members in the influencing group, and confirms that the number of members in the influencing group affects other individuals' behavior and emotion [20,21]. For instance, the presence of other customers in a shopping isle has a non-linear effect on shoppers' emotions and their likelihood of using store facilities [20]. Recent studies have paid closer attention to the social impact from user activities on social platforms [22–24], and considers the collective opinion expressed by users as an influence group [14]. For example, the number of user discussions on a movie's official Facebook page and the number of comments on YouTube videos both positively predict a movie's box office success [25]; the collective opinions on social media impact people's perception of the trustfulness of information and their likelihood of sharing the information [14]; in response to customer online complaints, the favorable experience-based defensive statements by other consumers along with the positive follow-up comments are effective in changing potential consumers' attitude towards a brand [26].

Drawing on Social Impact Theory, we examined the social impact created by Danmu. Danmu comments posted by viewers, whether synchronously or asynchronously, constitute an influence group. The total volume of comments, i.e., the number, could have an impact on online esports viewers' behavior. We tested whether Danmu, an interaction feature provided by online video platforms, serves as an effective tool to generate social impact. We further explored the differential impacts of Danmu comments on full-length competitive esports matches and video clips.

### 2.2. Studies on Danmu and Online Viewer Interaction

Compared with traditional in-person spectatorship, digital viewership occasionally lacks connectivity and interaction [27]. Online platforms have thus introduced real-time interactive features to fulfill consumers' desire for social interaction [11,28]. For example, social media and network sites now provide synchronous social interaction and media content distribution [29]. Through these services, viewers can communicate with other viewers using a chat function or a chatroom [30]. Viewers can thus instantaneously share their feelings and thoughts about the video content [3]. These real-time interactive features inspire greater social interaction among viewers while fostering a sense of community [10,31]. In addition, these services offer exciting and interactive features that are absent from conventional media [32], intensifying viewers' social well-being and satisfaction [11].

Compared with live chats where timeline-anchored comments are displayed in a scrolling list next to or beneath the video, Danmu embeds comments in videos. As a new internet interaction feature, Danmu has garnered extensive attention from scholars in multiple disciplines [12,13]. The present study is closely related to work exploring user behavior through a social interaction lens. Within this research stream, two Danmu-related issues have elicited great interest: why viewers watch videos with Danmu and how Danmu may affect viewer behavior. Danmu enables viewers to interact with each other by reading and referring to simultaneously posted comments [8]. Danmu thus creates an experience in which viewers feel as if they are watching and discussing a video with others [4]. Viewers appreciate the entertainment, information, feeling of companionship, and sense of belonging that Danmu offers [5–7,33,34]. Consequently, Danmu increases viewers' perceived social presence and cognitive presence [35]. These outcomes enhance video popularity [13] in addition to shaping viewers' loyalty to video-sharing platforms [4].

Research on viewers real-time interaction while watching online videos has tended to focus on users' propensity to use interactive features [35] and on users' perceived experiences and benefits [4,11]. Only a few studies have directly addressed the economic value of these interactive features [13]. We bridge this knowledge gap by using real-world data instead of survey inquiries to capture Danmu's impact on viewers' behavior. Hence, we are able to empirically compare how the intensity of Danmu comments influences the viewers' viewing behavior and engagement behavior differently.

### *2.3. Studies on Sport and Esports Demand*

The term "esports" refers to an organized video game competition. Esports spectators possess similar motives to traditional sport spectators [36,37]. Thus, findings regarding traditional sport consumers' behavior offer important insights into understanding esports consumer behavior. The economic literature on sport demand has referred to game attendance [38,39] and television ratings [40,41] to pinpoint demand factors. A large body of sport demand literature originated from Rottenberg [42], who distinguished a game's outcome uncertainty as a key driver of attendance [43,44]. Other studies have uncovered additional factors affecting attendance and television viewership, including team quality and talent [45–47], team rivalry [48,49], and team history [38,50].

Moreover, studies on traditional sport consumers explored consumers' fulfillment of social and psychological needs through the attending of sport events [51–53]. Sport venues and sport bars are legitimate sites for social interaction [54–57]. Online sport viewers relatedly wish to share feelings, thoughts, and information and to gain a sense of group membership [58]. Online fans therefore engage in conversation via a "second screen" [59] and live chats [11,58] while watching sport games. Online esports spectators also seek out socialization opportunities through esports consumption [37,60].

Regarding the online consumption of media content, researchers frequently consider click-based transactions (e.g., the number of views, shares) when evaluating demand [13,61,62]. Another form of click-based transaction, the number of "likes", serves as an important measure of consumer engagement [25,63,64]. Online consumer engagement can be characterized by the level of consumer input [65] and self-expression [25]. The "like" button enables users to express their support for the products; therefore, clicking the "like" button connects consumers to the product [25]. Users who click "likes" are more engaged [64], more likely to use the media content [28], and more likely to spend more on their "liked" products [64].

Compared with other video contents, the online nature of esports and esports viewers' desire for social interaction render esports a suitable context to explore the complex impact of Danmu comments. As a complement to the sport demand literature, we control for multiple sport demand factors to delineate Danmu comments' effects on esports online videos. Furthermore, we select two popular esports games to explore whether Danmu comments' impacts are affected by game-related characteristics.

## 3. Hypotheses Development

### *3.1. The Impact of Danmu Comments on the Behavior of Full-Length Match Viewers*

Social Impact Theory serves as an important theoretical foundation for the study of social viewership. The engagement in the same social environment during TV viewership affects viewers' perceptions of, feelings about, and attitudes toward the content [24]. Similarly, co-viewing TV programs with peers affects viewers' attitudes towards their consumption behaviors and lifestyles [23]. For digital viewership, Ang et al. find that the social presence and synchronicity in watching livestreaming induce a more authentic viewing experience and thus increase viewers' subscribing intention [22].

Studies on esports highlight viewer demand for socialization opportunities through game viewing [60,66]. Moreover, viewer demand is an interaction that they perceive as natural and resembling in-person interaction in the digital space [67]. Given Danmu's significance in amplifying the social and cognitive presence [35], we propose the following hypothesis in the context of professional esports matches.

**H1a:** *The number of Danmu comments has a positive impact on the number of views of full-length esports matches.*

**H1b:** *The number of Danmu comments has a positive impact on the level of viewer engagement upon watching full-length esports matches.*

### 3.2. The Moderating Effect of a Full-Length Match on the Impact of Danmu Comments

Esports viewers have a strong desire for social interaction. Danmu comments may also entice viewers into watching shorter esports video clips, such as season highlights and game reports, as well as into engaging upon watching these videos. Hence, we propose the following hypotheses.

**H2a:** *The number of Danmu comments has a positive impact on the number of views of esports video clips.*

**H2b:** *The number of Danmu comments has a positive impact on the level of viewer engagement upon watching esports video clips.*

Moreover, video-sharing platforms have to pay a substantial amount of fees for the right to broadcast and share full-length sport matches [68,69], while teams and leagues can upload short esports video clips even if the platforms do not obtain the relevant copyrights. Therefore, it is important for the platforms to understand whether Danmu comments have different effects on online viewers' behavior in full-length esports matches and video clips. This paper thus further investigates whether full-length matches moderate the impact of Danmu comments on online viewers' behavior.

Although the overall impact of Danmu comments on online viewers' behavior may be positive, the impact of Danmu comments may be complex. On one hand, Danmu can enrich viewers' perceived benefits by creating a co-viewing experience; on the other hand, Danmu comments may cover the screen and obscure viewers' line of sight [33], thereby detracting from the viewer experience. Intuitively, the sizes of these opposite effects may vary between full-length matches and shorter videos.

Viewers of sport competitions consume the core sport product, such as on-field performance and game outcomes, which are unpredictable [70,71]. Sport consumers are also motivated by the social interaction available during the watching of the sport [51,52,58]. Sport competitions thus provide viewers with a more intense emotional experience [70,72]. This leads to more pronounced social impacts of the Danmu comments in full-length matches than in shorter video clips, including the positive impact from the socializing environment and the negative impact from excessive interaction. This positive impact of the Danmu comments is expected to be stronger in affecting viewers' decisions to watch media content. The negative impact from excessive overlaid comments could hinder viewers' abilities to enjoy the video, and thus it is expected to be stronger in discouraging viewers to participate in post-viewing engagement. This negative impact is further amplified in full-length matches compared with video clips. For example, when Danmu comments are overloaded on the screen in the key moments of an esports match, viewers might annoyed or even frustrated for not being able to enjoy the play due to other viewers' activities. We thus propose the following hypotheses.

**H3a:** *Compared with esports video clips, the positive effect of the number of Danmu comments on the number of views would be stronger for full-length esports matches.*

**H3b:** *Compared with esports video clips, the positive effect of the number of Danmu comments on the level of viewer engagement upon watching would be weaker for full-length esports matches.*

## 4. Methodology

### *4.1. Data and Research Context*

Our data consisted of videos from Bilibili.com on two prominent esports games, League of Legends and Overwatch. League of Legends is a popular multiplayer online battle arena game where each player controls a character and kills enemies to earn points. Overwatch, on the other hand, is a first-person shooter game. While a number of esports games have gained huge popularity in China, given the availability of data, these two games appear most suitable for the purpose of our study. League of Legends has developed an established tournament structure, while Overwatch continues to regularly update its tournament structure and competition rules. As it is described in Table 1, these two games differ in their genre, history, and popularity. Comparing these games enabled us to assess the impacts of game-related factors on Danmu's effectiveness.

**Table 1.** Esports Games and Bilibili Channels.

| Game | Game Type | Bilibili Channel | Bilibili Subscribers | Sample Period | Full-Length Matches |
|---|---|---|---|---|---|
| League of Legends | Multiplayer Online Battle Arena (MOBAs) | League of Legends Live | 7,592,000 | 15 January 2018–22 May 2021 | League of Legends Pro League(LPL)<br>World Championship<br>Mid-Season Cup (MSC)<br>Mid-Season Invitational(MSI)<br>Rift Rivals |
| | | League of Legends | 2,411,000 | 6 September 2017–22 May 2021 | |
| Overwatch | First-Person Shooters (FPS) | Overwatch Live | 660,000 | 10 February 2019–23 May 2021 | The Overwatch League (OWL) |
| | | Overwatch | 126,000 | 11 September 2018–20 May 2021 | |

Bilibili.com hosts both official esports game channels and individual content producers. Videos posted by unofficial content producers vary substantially in their topics, styles, and qualities. To avoid variations in the aforementioned attributes that are hard to measure, we focused on official videos and gathered data from four official channels on Bilibili.com: two official channels that release full-length matches shortly after the matches are concluded, as well as some pre-game and post-game shows, and two official channels that release game-related videos, such as highlights, trailers, and news. For full-length matches, our data covered one domestic professional league (League of Legends Pro League) and four international tournaments (World Championship, Mid-Season Cup, Mid-Season Invitational, and Rift Rivals for League of Legends). Our data also contained full-length matches for one professional league, the Overwatch League, an international league with a regular season and playoffs. Table 1 lists leagues and tournaments as well as the four channels from which we acquired data.

Our data contained information on the total number of views, total number of "likes", and total number of Danmu comments on each video at the point of data collection. On Bilibili, registered users that have completed account verification can post Danmu comments. Users with different experience levels face different word limits: less experienced users can only post up to 20 characters, while more experienced users can write up to 100 characters in each comment. This policy is intended to prevent comments posted by scam accounts that could adversely impact other viewers' viewing experience. We also gathered other video-related information, including the date and time of video publication, video length, the number of labels attached to the video, and the number of characters in the video description.

We obtained team- and game-level performance information from Liquipedia.com and Wanplus.com. Liquipedia.com is a community-based English-language website that relies on user-contributed content. Wanplus.com is a Chinese website that collects game statistics through data mining. Wanplus.com also creates metrics that reflect esports performance and teams' market value. We identified each esports team's total number of wins and total number of losses in each league and tournament. We gathered the results of each match as well.

### 4.2. Econometric Models

We performed two sets of regression analyses to investigate the impacts of Danmu comments on viewers' viewing behavior and post-viewing engagement. In the first set of analyses, while controlling for team quality and game outcome, we examined the influence of Danmu comments on full esports matches. In the second model, we compared the influence of Danmu comments on full-length matches and on esports video clips.

#### 4.2.1. The Impact of Danmu Comments on the Behavior of Full-Length Match Viewers

When examining the behaviors of viewers of full-length esports matches, we are able to control for important sport demand factors, such as match quality and team quality. These factors, however, are not always present for short video clips, which may cover season previews or weekly summaries. In addition, platforms have to acquire copyrights to broadcast full-length sport matches [68,69], so it is important for the platforms to understand how Danmu comments may impact full-length match viewers' behavior. Therefore, we first focus on a subsample involving only the full-length esports matches. We estimated the following equations to explore factors influencing a full esports match's number of views and the number of "likes":

$$\begin{aligned} Log(View_{it}) = {} & \alpha_0 + \alpha_1 Team1_{nwin_{it-1}} + \alpha_2 Team2_{nwin_{it-1}} + \alpha_3 Nwin_{diff_{it-1}} \\ & + \alpha_4 \%Pt\_diff_{it} + \alpha_5 Log(Danmu_{it}) + \alpha_6 X_{it} + \epsilon \end{aligned} \tag{1}$$

$$\begin{aligned} Log(Likes_{it}) = {} & \alpha_0 + \alpha_1 Team1_{nwin_{it-1}} + \alpha_2 Team2_{nwin_{it-1}} + \alpha_3 Nwin_{diff_{it-1}} \\ & + \alpha_4 \%Pt\_diff_{it} + \alpha_5 Log(Danmu_{it}) + \alpha_6 X_{it} + \epsilon \end{aligned} \tag{2}$$

In Equation (1), $View_{it}$ denotes the total number of views for match i in season t on Bilibili. Similarly, in Equation (2), $Likes_{it}$ denotes the total number of "likes" on a given match. The number of views measures viewers' viewing behavior [61], and the number of "likes" measures viewer engagement upon watching the media content [25,63]. The dependent variables were log transformed in both equations. Our main variable of interest was the total number of Danmu comments per game ($Danmu_{it}$); this variable was also log transformed due to the large number of comments ($Log(Danmu_{it})$). To measure the quality of two competing teams, we included each team's net number of wins in the previous season for the same league or tournament ($Team1_{nwin_{it-1}}$ and $Team2_{nwin_{it-1}}$). The net number of wins was defined as the total number of wins minus the total number of losses by a team in a season. Following Rottenberg [42], who noted that outcome uncertainty can affect demand for a game, we measured the predictability of game results by the difference in teams' abilities. Specifically, we incorporated the absolute difference between the two teams' performance in the prior season ($Nwin\_diff_{it-1} = |Team1\_nwin_{it-1} - Team2\_nwin_{it-1}|$). The match result, measured by the percentage difference between the two teams ($\%Pt\_diff_{it}$), was included in our models as well. Because some matches involved a different number of rounds, we first took the difference in two teams' final points (i.e., rounds won) and then divided this figure by the total number of rounds played in the match.

In Equations (1) and (2), $X_{it}$ contains a set of esports game-level controls as well as video-specific information. Game-level controls included whether the game was a playoff game, qualifier, group stage, quarterfinal, semifinal, or final game. These controls conveyed the match's significance [38]. Video-specific controls included the length of the video measured in seconds, the number of characters in the video description, and the number of labels attached to the video.

#### 4.2.2. Moderating Effect of Full-Length Match on the Impact of Danmu Comments

In this analysis, we compared the effects of Danmu on full-length esports matches and esports video clips. The observations therefore covered all videos published by the four studied channels.

$$Log(View_i) = \beta_0 + \beta_1 Log(Danmu_i) + \beta_2 Fullgame_i + \beta_3 Log(Danmu_i) \times Fullgame_i + \beta_4 Top5_i + \beta_5 X_i + \epsilon \quad (3)$$

$$Log(Likes_i) = \beta_0 + \beta_1 Log(Danmu_i) + \beta_2 Fullgame_i + \beta_3 Log(Danmu_i) \times Fullgame_i + \beta_4 Top5_i + \beta_5 X_i + \epsilon \quad (4)$$

Similar to Equations (1) and (2), the dependent variables were the log-transformed number of views and number of "likes" of each esport-related video in Equations (3) and (4), respectively. $Log(Danmu_i)$ denotes the log-transformed number of Danmu comments overlaid on video $i$. $Fullgame_i$ indicates whether the video is a full esports match on Bilibili. We integrated an interaction term between $log(Danmu_i)$ and $Fullgame_i$ to determine whether Danmu comments influenced viewers of full-length match videos differently than viewers of esports video clips.

Among observations of esports video clips, we specified one additional video type, $Top5_i$ which indicates whether the video is a top 5 highlight that the official channels regularly feature. $X_i$ is a vector of controls. For League of Legends, we included six dummy variables to control for different leagues and tournaments discussed in a video—League of Legends Pro League, World Championships, Mid-Season Cup, Mid-Season Invitational, Rift Rivals, and all-star events. For Overwatch, we included four dummy variables to identify the Overwatch League, Overwatch Contenders, World Cup, and all-star events. Additionally, we controlled for whether the video involved a preseason, playoff, qualifier, group stage, quarterfinal, semifinal, or final game. All of these variables were created based on labels attached to the videos as well as the keywords extracted from video titles. Similar to Equations (1) and (2), we considered the length of the video, the number of characters in the video description, and the number of labels attached to the video. Lastly, we controlled for the year the video was published to capture year-specific characteristics in viewers' viewing behavior and the engagement behavior.

#### 4.2.3. Identification Strategy: Two-Stage Least Squares with an Instrumental Variable

The number of Danmu comments and the number of views were jointly determined in Equations (1) and (3). Viewers can only leave Danmu comments after watching at least part of a video. Hence, videos with a higher number of views are likely to include a larger number of Danmu comments. The number of Danmu comments is also likely to be endogenous in Equations (2) and (4) regarding viewers' engagement behavior; for instance, viewers who are more pleased with a video and click the "like" button are more apt to leave Danmu comments.

To address the endogeneity concern about the $Danmu_i$ variable, we employed two-stage least squares regressions with an instrumental variable [17–19]. We used the number of Danmu comments posted on the previous full-length match or videos from the same Bilibili channel as the instrument. An instrumental variable must satisfy two conditions: first, the instrument needs to be correlated with the endogenous variable; and second, the instrument needs to be uncorrelated with the error term. The volume of Danmu comments on a Bilibili channel was found to exhibit time series patterns; that is, the lagged number of Danmu comments was correlated with the number of Danmu comments on a given video. Conversely, the number of Danmu comments in the previous video was unlikely to affect the viewing behavior and post-viewing engagement behavior of the viewers of the current video. Therefore, the lagged volume of Danmu comments represented a valid instrument.

### 4.3. Summary Statistics

Table 2 displays the summary statistics of key variables included to estimate Danmu comments' impact on full esports matches (Equations (1) and (2)). Table 3 presents summary statistics for key variables in the analyses of the moderating effect of a full-length match on Danmu comments' impact (Equations (3) and (4)). The average number of views was much greater than the average number of likes for both League of Legends and Overwatch. In addition, the average number of Danmu comments was much larger for League of Legends than for Overwatch. This discrepancy is likely due to these games' disparate popularity. Moreover, for both games, the average number of Danmu comments was much greater for full-length matches than for the full sample. This distinction is presumably due to a full esports game's longer video length, but could also reflect viewers' desire to post Danmu comments while watching a full-length esports match.

**Table 2.** Summary Statistics of Full Esports Matches.

| | League of Legends | | | | Overwatch | | | |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** |
| $View_{it}$ | 520,772 | 1,011,874 | 12,211 | 20,735,433 | 53,164 | 67,567.14 | 1151 | 860,857 |
| $Likes_{it}$ | 6707 | 12,714.71 | 290 | 304,700 | 976.10 | 1238.03 | 82 | 23,787 |
| $Team1\_nwin_{it-1}$ | 1.90 | 6.26 | −15 | 17 | 0.16 | 9.02 | −17 | 25 |
| $Team2\_nwin_{it-1}$ | 1.12 | 6.52 | −16 | 17 | 0.48 | 8.58 | −17 | 25 |
| $Nwin\_diff_{it-1}$ | 5.82 | 5.54 | 0 | 32 | 10.57 | 8.26 | 0 | 38 |
| $\%Pt\_diff_{it}$ | 0.80 | 0.30 | 0.20 | 1 | 0.63 | 0.32 | 0.14 | 1 |
| $Danmu_{it}$ | 8494 | 17,188.80 | 46 | 343,987 | 1295.73 | 1705.13 | 3 | 18,898 |
| N | 1337 | | | | 749 | | | |

**Table 3.** Summary Statistics of All Esports-Related Videos.

| | League of Legends | | | | Overwatch | | | |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **Min** | **Max** | **Mean** | **SD** | **Min** | **Max** |
| $View_i$ | 273,914 | 737,324.10 | 184 | 20,735,433 | 38,715 | 84,316.89 | 925 | 2,478,910 |
| $Likes_i$ | 6473 | 18,963.26 | 8 | 554,856 | 886.10 | 1749.01 | 33 | 55,178 |
| $Danmu_i$ | 2915 | 9910.10 | 0 | 343,987 | 747.40 | 1485.77 | 0 | 18,898 |
| $Fullgame_i$ | 0.27 | 0.44 | 0 | 1 | 0.52 | 0.50 | 0 | 1 |
| $Top5_i$ | 0.11 | 0.31 | 0 | 1 | 0.06 | 0.24 | 0 | 1 |
| N | 5833 | | | | 1453 | | | |

## 5. Regression Results

### 5.1. Estimated Effects of Danmu Comments' Impact on the Behavior of Full-Length Match Viewers

Table 4 shows the regression results for Equations (1) and (2). The regression models of League of Legends included 1331 observations, and the regressions of Overwatch included 463 observations. These regressions mainly tested Danmu comments' effects on the number of views of full-length esports matches and viewer engagement after watching the games. Although we incorporated several control variables into this analysis, due to limitations in table space, we only reported estimates for the key variables of interest in Table 4. The main results demonstrate several intriguing patterns.

For both League of Legends and Overwatch, the estimated coefficients of $Log(Danmu_{it})$ were positive and statistically significant. Specifically, a 1% increase in the number of Danmu comments led to an approximate 0.66% increase in the number of views and a roughly 0.27% increase in the number of likes for League of Legends (vs. an approximately 0.92% increase in the number of views and about a 0.69% increase in the number of likes for Overwatch). These results highlight Danmu comments' positive impact on the number of views of a full-length match and viewers' post-game engagement irrespective of game type. This finding lends support to both H1a and H2a. This finding is also consistent with that of [8,13], who found the number of Danmu comments to be a major predictor of video popularity. Moreover, this positive effect of Danmu comments was stronger on the number of views than on the number of "likes". Viewers may choose to watch an esports match out of curiosity without being familiar with the match quality, such as teams' actual performance or the excitement of the match. A socially interactive environment would thus inform potential viewers' decision to watch. However, viewers' post viewing engagement was also heavily dependent on the video content; Danmu comments thus had a weaker influence on the number of "likes" than on the number of views.

**Table 4.** Estimated Effects on Full Esports Match Viewer Behavior.

| | **League of Legends** | | **Overwatch** | |
|---|---|---|---|---|
| | **Views** | **Likes** | **Views** | **Likes** |
| $log(Danmu_{it})$ | 0.6572 ***<br>(6.80) | 0.2722 **<br>(2.07) | 0.9225 ***<br>(13.13) | 0.6917 ***<br>(10.34) |
| $Team1\_nwin_{it-1}$ | 0.0232 ***<br>(4.61) | 0.0282 ***<br>(3.99) | −0.0011<br>(−0.63) | −0.0031<br>(−1.61) |
| $Team2\_nwin_{it-1}$ | 0.0188 ***<br>(4.66) | 0.0206 ***<br>(3.61) | −0.0020<br>(−0.82) | −0.0040<br>(−1.60) |
| $Nwin\_diff_{it-1}$ | −0.0053 **<br>(−2.12) | −0.0108 ***<br>(−2.86) | 0.0001<br>(0.06) | 0.0042<br>(1.64) |
| $\%Pt\_diff_{it}$ | 0.1660 ***<br>(3.48) | 0.4041 ***<br>(5.30) | 0.1365 **<br>(2.07) | 0.1212 *<br>(1.74) |
| Game-level Characteristics | Included | Included | Included | Included |
| Video Specific Information | Included | Included | Included | Included |
| Adjusted R-squared | 0.89 | 0.69 | 0.81 | 0.65 |
| N | 1331 | 1331 | 463 | 463 |

Notes: (1) t value in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; (2) The first game is dropped from the estimation due to the lack of a lagged variable; (3) All models include game-level characteristics and video specific information. Most of their estimation results are not statistically or economically significant. Due to space limitations, the estimated results on game-level and video specific control variables are not reported in this table.

As indicated in Table 4, the effect of esports performance varied between the two games. For League of Legends, the estimated coefficients of $Team1\_nwin_{it-1}$ and $Team2\_nwin_{it-1}$ were positive and statistically significant, implying that teams' performance in the previous season heightened both the total number of views and the total number of likes. Therefore, similar to traditional sport [45,47,73], team quality appeared to positively influence esports viewership. The variable measuring the difference in teams' performance, $Nwin\_diff_{it-1}$, was negative and statistically significant. Variation in team quality therefore reduced both the number of views and viewer's level of post-game engagement. When the quality difference between the two teams was large, the outcome of the game became more predictable. Hence, the negative estimated effect of the $Nwin\_diff_{it-1}$ variable substantiated the uncertainty of the outcome hypothesis [42] in the esports setting. Meanwhile, the estimated coefficient of $\%Pt\_diff_{it}$ was positive and statistically significant, implying that viewers preferred to watch an esports match with wider result margins.

By contrast, for both estimations involving Overwatch, none of the estimated coefficients of $Team1\_nwin_{it-1}$, $Team2\_nwin_{it-1}$, or $Nwin\_diff_{it-1}$ was statistically significant. More precisely, neither team quality nor outcome uncertainty affected the viewership of Overwatch games or the viewer engagement after the game. These discordant findings on the effect of sport performance may result from the difference between the two games. Having launched its first professional tournament in 2011, League of Legends boasts more comprehensive rules of play and a more stable tournament structure. Overwatch had its first professional season in 2018 and has continued to update its tournament structure as well as other features each season. Overwatch League teams thus have much less competitive experience, such that their past performance holds less predictive power for future performance. As in studies of traditional sport, teams with a longer history enjoy a larger loyal fan base and stronger game demand [38,50]. The Overwatch League, as a rising esports league, is likely to have relatively more new viewers with limited knowledge of teams' quality and past performance. Consequently, neither teams' past performance nor performance-based differences affected the number of views and number of "likes". However, the coefficient of $\%Pt\_diff_{it}$ was positive and statistically significant, echoing the findings for League of Legends: viewers again favored an esports match with larger result margins regardless of game type.

### 5.2. Estimated Moderating Effect of Full-Length Match on the Impact of Danmu Comments

Table 5 outlines the estimation results of Equations (3) and (4), which estimate the moderating effect of full-length match on the impact of Danmu Comments. When including all esports video clips, such as match or season highlights and game reports, our sample for League of Legends had 5881 observations and our sample for Overwatch had 1452 observations. For esports video clips that were rarely match-specific, unlike Equations (1) and (2), variables used to assess competing teams' past performance and match outcomes were excluded from these estimations.

**Table 5.** Estimated Moderating Effects of Full-length Match on the Impact of Danmu.

| | League of Legends | | Overwatch | |
|---|---|---|---|---|
| | **Views** | **Likes** | **Views** | **Likes** |
| $log(Danmu_i)$ | 0.7044 ***<br>(42.06) | 0.5912 ***<br>(33.69) | 0.4263 ***<br>(9.24) | 0.3055 ***<br>(8.18) |
| $Fullgame_i$ | −1.3940 ***<br>(−3.69) | 0.8206 *<br>(1.95) | −2.4490 ***<br>(−6.55) | −1.7820 ***<br>(−5.51) |
| $log(Danmu_i) \times Fullgame_i$ | 0.1241**<br>(2.49) | −0.2540 ***<br>(−4.038) | 0.3054 ***<br>(4.51) | 0.1737 ***<br>(3.04) |
| $Top5_i$ | 0.2713 ***<br>(10.21) | 0.0769 **<br>(2.57) | 0.4707 ***<br>(6.94) | 0.3008 ***<br>(5.51) |
| Game-level Characteristics | Included | Included | Included | Included |
| Video Specific Information | Included | Included | Included | Included |
| Adjusted R-squared | 0.82 | 0.79 | 0.79 | 0.70 |
| N | 5881 | 5881 | 1452 | 1452 |

Notes: (1) t-value in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; (2) Two observations are dropped due to the lack of observation for the lagged variable in the first observation; (3) All models include game-level characteristics and video specific information. Most of these estimates are not statistically or economically significant. Due to space limitations, these results are omitted from the table.

The results revealed more striking impacts from Danmu comments. The estimated coefficients of $Log(Danmu_i)$ were positive and statistically significant in all models, implying that Danmu comments could increase the total number of views and the total number of "likes" for video clips of both games. These results support both H2a and H2b. Moreover, the coefficients of the interaction between Danmu comments and full-length matches, $Log(Danmu_i) \times Fullgame_i$, were positive and statistically significant in the estimations of the number of views for both games. In other words, compared with video clips such as highlights and game news, Danmu comments played a greater role in increasing the number of views of full-length esports matches, which lends support to H3a. Regarding the estimations of viewers' post-viewing engagement, whereas the estimated coefficient of $Log(Danmu_i) \times Fullgame_i$ remained positive for Overwatch, it was negative in the League of Legends regression. Therefore, H3b is only supported in the analysis of League of Legends.

Overall, Danmu can create an immersive experience and enhance viewers' perceived benefits by promoting social interaction [4]. However, an overly high number of Danmu comments can limit observers' view of the screen [33], making the viewing experience less enjoyable. The intensified emotional experience during competitive game viewing [70,72] can amplify both the positive and negative influences of Danmu comments. When viewers were simply deciding whether to watch an esports-related video, the positive impact of a socially engaged viewing environment outweighed the negative impact from excessive interaction. Hence, compared with video clips, the positive impact of Danmu comments on the number of views is greater that on full-length matches. Contrarily, viewers' post watching engagement can be affected by their in-video viewing experience. League of Legends, a popular game with a large loyal fan base, usually received many Danmu comments, which can obscure viewers' line of sight [33]. Such an adverse impact of Danmu comments can manifest in a competitive match's viewing environment, leading to a negative estimated coefficient on the $Log(Danmu_i) \times Fullgame_i$ variable. Overwatch is a comparatively new game with fewer loyal fans. Many viewers are less familiar with this game and derive more pleasure from interacting with other viewers. Therefore, for Overwatch, we still observed an overall positive moderating effect of full-length match on the positive impact of Danmu on viewers' post-viewing engagement.

The $Fullgame_i$ dummy variable was negative and statistically significant in the estimations on the number of views for both games. It was also negative and statistically significant in the estimation on the number of "likes" for Overwatch. Thus, the number of views on video clips was higher than the views on full-length matches, conditioned on other video-specific characteristics. Official game channels regularly publish the top 5 weekly, monthly, and season highlights, as reflected by the $Top5_i$ dummy variable. The estimated coefficients of this variable were positive and statistically significant in all regressions.

## 6. Discussion and Conclusions

We explored the social impacts generated from Danmu, a novel online social interaction feature, on the behaviors of viewers of online videos. Specifically, we considered two popular esports games (League of Legends and Overwatch) while controlling for traditional sport demand factors to identify Danmu comments' impact.

We first limited our analysis to full esports matches to explore the effects of Danmu comments on the number of views of full-length matches and post-game viewer engagement. The results suggested that the volume of comments in the form of Danmu, which can generate an atmosphere well-suited to social interaction and increased viewers' perceived social and cognitive presence [35], improved both the number of views of full-length esports matches and the level of post-viewing viewer engagement. Danmu comments demonstrated stronger positive impact in attracting viewers to watch a full esports match than encouraging them to participate in post-viewing engagement.

To compare the impact of Danmu on full esports matches with its impact on video clips, we subsequently expanded our sample to cover all videos released by the official game channels. Danmu comments similarly improved the number of views and the level of post-viewing viewer engagement for esports video clips. Moreover, Danmu comments had a stronger positive effect on the number of views of full-length matches than of video clips. However, for League of Legends, compared to viewers of video clips, Danmu comments demonstrated a weaker positive impact encouraging full-length match viewers to engage upon watching.

Our results present valuable insight into viewers' decision-making processes when consuming online media content. Potential viewers may perceive Danmu comments as an opportunity to socialize. A higher number of Danmu comments thus makes online videos more appealing to potential viewers. However, intensive in-video discussion may not necessarily correspond to high video quality. Even with myriad socialization opportunities, a poor-quality video or uninteresting content will not satisfy viewers. Thus, the positive impact of Danmu comments appears weaker on viewer's engagement behavior than on their viewing behavior. Moreover, as a means of creating in-video interaction, Danmu has benefits and drawbacks. On one hand, Danmu can enrich viewers' perceived benefits by creating a co-viewing experience; on the other hand, Danmu comments may cover the screen and obscure viewers' line of sight [33], thereby detracting from the viewer experience. This disadvantage has a more pronounced effect on the viewers' engagement post-watching than in attracting potential viewers.

We further discovered that content-specific characteristics may influence Danmu comments' effectiveness in affecting viewer behavior. Danmu comments play a prominent role in boosting the number of views on full-length media content about novel topics compared with content that has a longer history and an established viewer base. With limited information otherwise, the number of Danmu comments can pique potential viewers' curiosity for esoteric content.

Our study has several important theoretical implications. While our study affirms the applicability of Social Impact Theory in studying digital social viewing [22], we extended the application of the theory by testing the social impact created through Danmu on two types of behavior, viewers' decisions to watch, i.e., the number of views, and viewers' decisions to engage post-watching: the number of "likes". Our findings highlight the differential impact of Danmu on viewer's viewing behavior and engagement behavior. Our findings also uncover conditions under which social impact factors lead to different levels of positive outcome.

Our research also offers practical guidance for video-sharing platforms whose revenues are heavily dependent on viewership and viewer experience. First, these platforms should acknowledge the importance of improving social interaction in online viewership and the effectiveness of Danmu in creating virtual socialization opportunities. Video-sharing websites in other markets, especially those that target a younger generation of viewers who usually demand a sense of belonging and community through online viewing, could thus consider introducing this type of social interaction tool that is pervading platforms in Asia. Second, since excessive viewer interaction can potentially hamper their experiences, platforms should incorporate Danmu with caution. For example, platforms could set a maximum number of Danmu comments that could be overlaid on the screen. Platforms could also develop and strengthen Danmu policy and guidelines to ensure that inappropriate comments such as harassment, cyberbullying, and scams are forbidden. Lastly, platforms need to take into consideration the characteristics of the video content while employing the Danmu feature, as the impact of Danmu could vary by the media content.

This research has several limitations that leave room for future work. First, our paper solely considers the volume of Danmu comments. The content of the comments also likely affects other viewers' behavior. For example, heated discussions with arguments and conflicts could have vastly different impacts on viewer behavior than friendly and engaging discussions. Future research could examine not only the volume, but also the topic and sentiment of Danmu comments in order to obtain a more comprehensive understanding of the social impact from Danmu. Second, our data source, Bilibili.com, does not publish viewer information. Although we endeavored to provide evidence on the roles of viewer characteristics by comparing two esports games with varying popularity and history, we could not directly test whether viewers' personal knowledge of and experiences with the video content colored Danmu's effects. Subsequent studies can refer to data on viewer-oriented information to more thoroughly investigate the factors contributing to the viewership of online videos and post-viewing engagement. Lastly, the anonymous nature of Danmu comments warrants further careful examination. On one hand, anonymous Danmu comments enable viewers to express their spontaneous and honest opinions. On the other hand, such anonymous communications are more likely to prompt false information or messages that are not properly vetted. Future work could investigate the trustworthiness of Danmu comments and how they impact other viewers' behavior.

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