Determinants of Esports Highlight Viewership: The Case of League of Legends Champions Korea

Hyunwoong Pyun
College of Sport Science
Sungkyunkwan University
hwpyun@skku.edu

Wonseok (Eric) Jang
College of Sport Science
Sungkyunkwan University
wjang@skku.edu

Gyemin Lee
Department of Electronic and IT Media Engineering
Seoul National University of Science and Technology
gyemin@seoultech.ac.kr

Yoonji Ryu
College of Sport Science
Sungkyunkwan University
blessryu@gmail.com

Hui Hwang
College of Sport Science
Sungkyunkwan University
huizzang@g.skku.edu

Jaehyun Jeong
College of Sport Science
Sungkyunkwan University
wogus1770@g.skku.edu

Abstract

Studies on esports league demand via new media platforms are limited yet. This paper is the first to identify determinants of esports highlight viewership. Using set-level highlight view count from YouTube, we analyze various determinants to explain view counts. As a result, we found that the number of kills, playoff games, age of video clip, 2nd round games, and 3rd set is positively correlated to view counts. Outcome uncertainty and upset results do not affect view counts. We interpret the results that as highlight clips are released after the game is finished, viewers can know the results when making a decision. Or, relatively short highlight videos reduce opportunity costs for fans and fans do not care about game outcomes much.

Keywords: esports, highlights viewership, League of Legend, LCK, outcome uncertainty

1. Introduction

Esports has been identified as one of the fastest-growing professional sports industries in the world. In 2020, the total number of esports viewership has reached close to 500 million and the total estimated revenue in the whole esports industry was around 160 billion US dollars (Newzoo, 2020). This rapid growth of esports seems to be from a successful attachment to social live streaming services (SLSS, such as Twitch and YouTube). Unlike traditional professional sports, esports games are mostly broadcasted by SLSS, not traditional TV service.

Along with the rapid growth of esports industry, studies on esports have been conducted recently. The existing research of esports mostly focus on the concept of esports (Sjöblom & Hamari, 2017; Wagner, 2006), motivations for watching esports (Brown et al., 2018; Xiao, 2020), an individual game streamer (Xu et al., 2022; Li et al., 2020) the relationship between game playing and watching game streams (Jang et al., 2021; Jang & Byon, 2020), and parasocial interactions in SLSS (Leith, 2021; Wulf et al., 2021). However, studies related to esports league viewership are yet limited.

The popularity of SLSS gives more various choices, in terms of which video clips to watch, to consumers. As a result, demands for highlight videos emerge and increase as consumers want to watch many video clips with limited time constraint (Park et al., 2018). For the broadcaster side, highlight videos are commonly used for attracting new viewers and reminding casual viewers to watch regularly (Bae & Kim, 2020). Video highlights are also popular in professional sports since fans have physical restrictions to watch every game in real-time (McCammon, 2021).

While the majority of esports fans are young male (Sjöblom & Hamari, 2017), these young fans, namely "generation Z", are not interested in watching live games much compared with old fans of traditional sports (Silverman, 2020). As a result, the consumption pattern of esports league is changing, from TV to mobile device, from live games to highlights. Thus, the key to understanding esports league fans would be to identify determinants of online highlight viewership, not viewership of the live game.

URI: https://hdl.handle.net/10125/103109
978-0-9981331-6-4

Therefore, this paper explores determinants of esports online highlight viewership. Focusing on League of Legend Champions Korea (LCK), one of the most popular esports leagues in the world, this paper successfully identifies determinants of highlight viewership; the number of kills, playoff games, age of video clip, 2nd round games, and 3rd set are positively correlated to view counts. Outcome uncertainty and upset result do not change viewership. The results shed a light on a deeper understanding of esports fan demand and online viewership and have practical implications to esports industries.

2. Contextual Background

2.1. Esports

Esports research is a growing topic among sport, game, and communication scholars in recent years. As mentioned earlier, the extant research about esports mostly focused on the motivation of esports consumers. There are some empirical studies trying to figure out the differences and similarities between esports and traditional sport consumer behavior (Brown et al., 2018; Lee & Schoenstedt, 2011). Brown et al. (2018) aimed to delineate esports consumption, traditional sports consumption and a contrast between them. More than 1,300 esports consumers answered the survey about uses and gratifications obtained when consuming esports and mediated traditional sports. The results suggested that esports consumers sought out media for both esports and traditional sports for similar motivations, specifically social support, fanship, and Schwabism, a form of information gathering intended to help one become more knowledgeable about sports (Ruihley & Hardin, 2011).

There are some studies which paid attention to the phenomena of esports streaming and streamer (Leith, 2021; Wulf et al., 2021). Wulf et al. (2021) were interested in parasocial interactions (PSI) with videogame streamers of Twitch, one of the most popular game streaming platforms. Result showed that the more individually participants were addressed and whether the streamer reacted to messages in the chat affected experiences of PSI.

Another stream of esports research is about the relationship between game playing and watching games streams (Jang et al., 2021; Jang & Byon, 2020). Jang and Byon (2020) found a significant and positive relationship between esports gameplay and esports media consumption. This indicates that people who consume esports recreational gameplay are likely to consume esports event media. Later, Jang et al. (2021) classified esports media consumption into two distinct categories; streamers' esports live streaming content and esports event broadcast. They examined the mediating effect of esports content live streaming in the relationship between esports gameplay and esports event media. The result showed that the intention of consuming esports content live streaming fully mediated the relationship between esports recreational gameplay and esports event broadcast consumption.

In order to advance the understanding of esports consumer behavior, more scholars analyzed motivations and antecedents for the esports consumption itself (Sjöblom & Hamari, 2017; Xiao, 2020). Sjöblom and Hamari (2017) conducted an online survey and sampled esports viewers from the platforms of Reddit, Facebook, Twitter, and other game-related forums. The result showed that the acquisition of knowledge was one of the positive predictors of esports viewership. This suggests that watching esports games is a way for spectators to learn about teams/players and their styles of play. Xiao (2020) also explored the factors that correlate with the behavior intentions of watching esports based on the theory of reasoned action. The findings revealed that three behavior beliefs-related factor (aesthetics, drama, and escapism) and subjective norms positively associated with attitude toward watching esports.

In general, earlier esports literature conducted surveys and interviews from esports fans to understand esports consumer behavior (Qian et al., 2020; Xiao, 2020). Recently, more scholars are interested in empirical studies that analyze factors affecting esports viewership using esports game-level data (Watanabe et al., 2022).

2.2. Fan Demand of Traditional Sports

Most literature on sports fan demand focused on live attendance. In the literature, many factors have been identified as determinants of attendance demand. The quality of a match, such as a league standing (Benz et al., 2009) and total league points (Buraimo & Simmons, 2008; DeSchriver et al., 2016) has been used to control team performance on fan demand. In general, a better-performed team drives more attendance. Additionally, star players and players' salaries have also been reported to affect attendance demand positively (Humphreys & Johnson, 2020; Jewell, 2017; Sung & Mills, 2018). Matchday characteristics, such as the day of the week (Buraimo & Simmons, 2008), game time (Krumer, 2020), weather (Ge et al., 2020), and the geographical distance between competing teams (Humphreys &

Miceli, 2020), are commonly used as determinants of sports demand.

Fan preference toward outcome uncertainty has been popularly studied in the literature. The uncertain outcome hypothesis, based on Rottenberg (1956), explains that fans will prefer the unexpected outcome compared to the expected one; the attendance will be maximized when the win probabilities of home and away teams are equally distributed. On the other hand, Coates et al. (2014) applied the reference-dependent preference with loss averse agent (RDPLA) to fans' preferences toward outcome uncertainty; specifically, fans prefer certain outcomes to uncertain ones as they do not want to have a large chance of getting disutility from an unexpected loss than the extra utility from an expected win (i.e., loss averse) when the outcome becomes more uncertain. Empirical results have reported mixed evidence so far; Some findings support the UOH (Benz et al, 2009; Jang & Lee, 2015; Knowles et al., 1992; Owen & Weatherston, 2004a, 2004b; Rascher, 1999; Rascher & Solmes, 2007), whereas others support the RDPLA (Beckman et al., 2012; Coates & Humphreys, 2010; Coates et al., 2014; Cox, 2018; Czarnitzki & Stadtmann, 2002; Forrest et al., 2005; Forrest & Simmons, 2002; Lemke et al., 2010; Pawlowski, 2013; Sung & Mills, 2018).

Studies on live TV viewership follow. Forrest et al. (2005) tested fan preference on outcome uncertainty using the number of audiences for more than 500 English Premier League games. Allan and Roy (2008) examined the relationship between TV viewership and live attendance. Hausman and Leonard (1997) and Kanazawa and Funk (2001) tested superstar effects and racial discrimination using TV ratings for NBA games, respectively. Paul and Weinbach (2007) and Tainsky (2010) assessed demand for NFL broadcasts and outcome uncertainty, Alavy et al. (2010) covered minute-by-minute viewership to test the outcome uncertainty. Cox (2018) explored the difference between live attendance and TV viewership using England Premier League games.

In general, empirical evidence from using TV viewership has reported somewhat different preferences compared to live attendance. Usually, live attendees are regarded as a fan of the home team who prefer the home team win strongly even though there might be some neutral or away fans in the stadium. However, TV viewership does not have this restriction, viewers can be anyone who may live in a home team city with a strong preference for the home team, or some other region without preference, even including international fans. Due to this reason, the difference in empirical evidence between live attendance and TV viewership exists (Cox, 2018; Feddersen & Rott, 2011).

2.3. Sports Highlight Demands

While sports highlight or post-game show has a quite long history in traditional TV service, limited studies have focused on the viewership of highlight. Existing literature can be categorized into two lines of research; (i) studies focusing on the factors affecting the viewership (Dietl et al., 2003, Han et al., 2021; Salaga et al., 2021) and (ii) studies analyzing the relationship between the highlight viewership and the TV viewership (Bae & Kim, 2020).

Dietl et al. (2003) assessed determinants of highlight show viewership of German Bundesliga, and Salaga et al. (2021) looked at pre-game, the actual game, and post-game viewership separately. Specifically, they categorized determinants into four parts; anticipated characteristics, temporal characteristics, substitutes and weather, and actual characteristics. For the pre-game demands, they excluded actual characteristics since the variables for actual characteristics are only applicable to the actual game and post-game.

Han et al. (2021) covered the number of viewership of highlight video clips Korean soccer league and identified some important determinants of online highlight viewership, such as the importance of the game, whether derby match or not, in-game performance, and age of the highlight video clips. At the same time, they failed to cover other determinants, such as fan preference on outcome uncertainty and the difference between reference and the actual outcome.

Demand for esports leagues is also out of the spotlight in the academic field. Few recent studies tried to explain esports industry (Newman et al., 2022) and esports viewership (Watanabe et al., 2021).

2.4. Present Study

Given the circumstances that the highlights are generated after the live game, we divide highlight determinants into two categories; before the game factors and after the game factors. Factors determined before the game starts include team-related factors, uncertainty of outcome, and schedule-related factors. While these factors are examined in previous literature on live attendance and TV viewership, the impact of them on highlight viewership is not tested well. Factors determined after the match finished are related to the content of the game, including the game outcomes, the upsets, in-game statistics, and the duration of the competition. In the line with the reference-dependent preference with loss aversion, much literature reports unexpected game outcomes, especially unexpected losses, generate emotional cues for fans that trigger the next behavior (Card & Dahl, 2011; Munyo & Rossi, 2013). Also, the deposition theory explains that the enjoyment from watching game depends on an emotional investment on favorite team with preferred game outcome (Raney, 2013). Therefore, we include game outcomes and the upset results in our analysis.

3. Empirical Methods

3.1. Data

This paper explores the highlight viewership of the League of Legend Champions Korea (LCK) league. The League of Legends (LoL) was released in 2009 by Riot Games and has become the most popular video game in the world. Based on this popularity, several professional leagues depending on geographical location have been formed and the LCK league is one of the four major LoL leagues in the world. Currently, 10 teams participate in the LCK league and each team plays double round-robin tournaments (18 rounds with 10 teams) as a regular season. After the regular season, the top 6 teams go to the postseason, and the final winner of the postseason is awarded the championship of the league. Each game consists of 3 sets (best of 3) in the regular season and 5 sets (best of 5) in the postseason. LCK league hosts two regular tournaments each year (Spring and Summer), and every tournament contains around 100 games.

Table 1. Summary statistics

Variable	Mean	Std.Dev.
View Count	184,946	151,178
# of Kills	0.69	0.24
Uncertainty	2.46	2.27
Upset	0.34	0.48
Playoff	0.06	0.24
Game Time	33.47	5.89
Starting Time	0.48	0.5
Weekend	0.44	0.5
Age of Clips	593.19	338.12

LCK league runs a YouTube channel and posts set highlight videos after every game is finished. We collect the number of view count of each set highlight video clip from the YouTube LCK channel via YouTube API. From 2019 LCK Spring to 2021 LCK Summer, we collect 1496 set highlight viewership of 6 tournaments and 564 games.

For game-level data, we collect the length of game time and the number of kills both teams recorded in each set and the data is from https://lol.inven.co.kr/. We collected betting odds for each game from https://www.oddsportal.com as a proxy for game uncertainty. Unlike traditional sports, esports game does not have a home and away team, we use the squared difference between two betting odds as an uncertainty measure following Buraimo and Simmons (2015); the smaller the difference is, the greater the uncertainty is. We generate $upset$ variable which is equal to 1 when a weaker team from betting odds won. We generate $playoff$ dummy which is equal to 1 for the postseason games. We collect game day characteristics, such as day of the week (either weekend or not) and starting time (either before 6 pm or not). We also collect the difference between the posted date and to collected date as the age of the highlight clip.

Table 1 shows summary statistics of variables. The average view count is 184,947. Averagely 0.69 kill occurs per one minute. The difference in betting odds is 2.46, and 34% of game outcomes were unexpected. Playing time of a set is around 33 minutes, raged from 16.9 to 70.2 minutes.

3.2. Analysis

To explore the determinants of LCK league set highlights view count, following empirical model is formed.

$$\ln(viewcount)_{ijsdt} = \beta_0 + \beta_1 kills_{sdt} + \beta_2 uncertainty_{sdt} + \beta_3 upset_{dt} + \beta_4 playoff_{dt} + \beta_5 gametime_{dt} + \beta_6 staringtime_{dt} + \beta_7 weekend_{dt} + \beta_8 clipage_{dt} + \beta_9 2ndhalfround_{dt} + \beta_{10} set_{sdt} + \alpha_i + \theta_j + \lambda_t + u_{ijsdt} \quad (1)$$

where $viewcount_{ijsdt}$ is view count of LCK league game for team i and j, set s of game d, in the season t. $kills$ indicates the number of kills per minutes to capture in-game performance. $uncertainty$ is the difference in betting odds for two team as a proxy of game uncertainty. $upset$ is equal to 1 when weaker team beat stronger team. $playoff$ is equal to 1 for playoff games and $gametime$ is the length of playing time in minutes in set s. $startingtime$ is equal to 1 for a game starting over 6 pm. $weekend$ is equal to 1 for weekend games. $clipage$ is the age of highlight video clip. $2ndhalfround$ is equal to 1 for games in the second half round within a tournament, and set indicate set-specific fixed effects (from 1 to 5 sets). α_i and θ_j are team i and j fixed effect, λ_t captures tournament fixed effect. u_{ijsdt} is a heteroscedastic unobservable error term. The equation error term was assumed to be correlated within the team, and we clustered and standard errors accordingly. Using R and RStudio, we perform multi-level (team i and j, and tournament) least square dummy variable (LSDV) regression.

4. Results and Discussion

Table 2 shows the main results of logged view count from Equation 1.

As shown, the number of kills per minute is positively associated with view count. One more kill per minute increases view count by 30%. LCK fans prefer offensive games with more kills rather than defensive games. This result is consistent with previous findings of a positive association between in-game performance and game attendance (Han et al., 2021; Johnson, 2021).

Estimated coefficients on game uncertainty and upset are not statistically significant. Either game expectation or unexpected outcome does not alter the watching decision. The results are not consistent with previous findings on live attendance (Beckman et al., 2012; Besters et al., 2019; Martins & Cró, 2018; Sung & Mills, 2018) and TV viewership (Cox, 2018; Paul & Weinbach, 2007; Tainsky, 2010). However, this paper focuses on highlight view count, and highlight clips are produced after the game, and viewers are able to know the result before watching, unlikely live attendance, and live TV viewership. Or, relatively short highlight videos reduce opportunity costs for fans and fans do not care about game outcome much. Han et al. (2021) found consistent evidence with our results using the highlight view count of the Korean soccer league.

Playoff game drives more view count as expected; view count increases by 71% for playoff games. One minute increase in set playing time increases view count by 1.6%. This may indicate that fans do not prefer longer games, so if a game or set gets longer, they stop watching a live game and watch highlights later. Or, the longer game may be interpreted as a high-quality game, possibly with a come-back win. Fans may want to watch highlights to enjoy a come-back win later even though they watched a live game.

Fans do not have a preference for a weekend and late-night game. Since watching highlight clips from YouTube does not have any restrictions, in terms of time and location, fans may not react to game date and time. This may also indicate that live game viewership is not correlated with highlight viewership, since previous evidence on live game viewership often reported the different preferences in weekend and game time. It is quite obvious that older highlight clips have more view count since they were posted longer time to the public.

Table 2. Empirical results

Dependent Variable: Logged View Count		
Variables	**Estimate (*t*-value)**	***p*-value**
# of Kills	$.2997^{*}$ (.1289)	.020
Game Uncertainty	$.0295$ (.0219)	.177
Upset	$-.0555$ (.0794)	.485
Playoff	$.7111^{***}$ (.1602)	<.001
Playing Time	$.0158^{***}$ (.0031)	<.001
Starting Time	$.0819$ (.0762)	.282
Weekend	$.0163$ (.0494)	.741
Age of Clip	$.2689^{***}$ (.0355)	<.001
2nd Half Tournament	$.2868^{***}$ (.0670)	<.001
2nd Set	$-.0525^{*}$ (.0258)	.041
3rd Set	$.1529^{***}$ (.0465)	<.001
4th Set	$-.2351$ (.1425)	.099
5th Set	$.4598$ (.2443)	.059
Team Fixed Effects	yes	
Tournament Fixed Effects	yes	

Notes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$
Cluster-corrected standard errors at team level in parentheses.

Fans prefer the second half tournament compared to the first one since league standings and playoff appearances are determined later in the season. Compared to the first set view count, the second set view count decreases by 5.2%, and the third set view count increases by 15%. This is because the result of the third set determines the winner of the game in the regular season (best of 3). Estimated coefficients on the 4th and 5th set were not statistically significant. These results reflect that only playoff games go over the 5th set if necessary and only 6% of total games were playoff games, so the impact of the 4th and 5th set was not identified well.

Though the results of team fixed effects and tournament fixed effects are not reported in Table 2, there are some remarkable findings to report. In the LCK league, the T1 is well known as the most popular team. Compared to the reference team (APK), the view count for the T1 game increases by more than 100%. It seems that the popularity of the LCK league hugely relies on one team. Also, compared to the oldest tournament in the sample, 2019 LCK summer, highlight view count consistently rises, from 200% to 380% for the most recent tournament. Full results of fixed effects are available upon request.

Table 3. Robustness check

Dependent Variable: View Count		
Variables	**Estimate (*t*-value)**	***p*-value**
# of Kills	$71{,}508^{*}$ (21,055)	<.001
Game Uncertainty	$1{,}350$ (1,632)	.408
Upset	$-19{,}963$ (17,742)	.260
Playoff	$105{,}680^{***}$ (25,977)	<.001
Playing Time	$2{,}794^{***}$ (640)	<.001
Starting Time	$17{,}319^{*}$ (8,834)	.049
Weekend	$9{,}471^{*}$ (4,639)	.041
Age of Clip	$38{,}159^{***}$ (7,909)	<.001
2nd Half Tournament	-248 (5,826)	.965
2nd Set	$-14{,}788^{*}$ (6,582)	.024
3rd Set	$23{,}952^{***}$ (5,511)	<.001
4th Set	$11{,}432$ (50,503)	.820
5th Set	$180{,}132^{*}$ (98,869)	.068
Team Fixed Effects	yes	
Tournament Fixed Effects	yes	

Notes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$
Cluster-corrected standard errors at team level in parentheses.

As a robustness check, we performed the same analysis using view count (not log-transformed) to test whether our results are sensitive to log transformation. Table 3 shows the results of the robustness check.

As shown in Table 3, the results of the robustness check look similar to the original results in general. The number of kills per minute, playoff games, playing time, age of clip, and 3rd set are positively associated with view counts as shown in Table 2. Game uncertainty and upset do not alter view counts either. On the other hand, late-game and weekend game records highlight view count here. Also, more view counts for 2nd half tournament games are not reported here.

Overall, the determinants of highlight view count are consistently found in the robustness check except for preference for weekend games, late games, and 2nd round games.

5. Conclusion

This paper is the first to identify the determinants of LCK league set-level highlight view counts. Using set-level highlight view count data from the LCK channel on YouTube, we found that the number of kills, playoff games, playing time, age of clip, 2nd half tournament games, and 3rd set is positively associated with view count. Outcome uncertainty and the difference between expectation and the actual game outcome do not alter view counts. The most popular team in the LCK league, the T1, drives more than 100% view counts compared to the average team and view counts grow by season and tournaments. The results were not sensitive to log transformation of the dependent variable.

The empirical findings of this study provide significant theoretical value to academia that esports highlight demands are different from live attendance and TV audience demands. One of the key findings is that the highlight viewer does not respond to game uncertainty and upset results. As Han et al. (2021) noted, this difference might be due to the reason that highlight viewers decide to watch highlight clips after the game is finished, so they know the game results already. Or, since highlight clips are usually short, around 10 minutes on average, viewers may face lower opportunity costs and choose to watch video clips more easily.

The findings of this study can be used as guidelines for highlight clip providers. Recently, demand for highlights is increasing among sports fans so many sports leagues such as the National Basketball Association, the National Hockey League, and the Korean Baseball Organization provide highlights using artificial intelligence (AI) to meet the high demands. AI highlight is a technology-based automated highlight video clip generated without a human editor so that the high number of clips can be generated in a short time. The results of this study can be used as a direct basis for developing AI algorithms and are believed to be of great help in generating customized highlights for esports fans.

Further research is needed to have more practical implications. As Bae and Kim (2020) found, highlight viewership often leads to live game viewership and the LCK league may be able to attract new fans using highlight videos. However, the link between highlight viewership and live game viewership is not covered in this study due to the data limitation. While YouTube is one of the most popular SLSS services in Korea, there are many other similar services such as Twitch and Afreeca TV. The quality of the highlight video also affects watching decisions but it was not considered in this study. Lastly, there are more potential determinants that we could not include in the model due to the limitation of data accessibility. Future research needs to further consider more factors such as star players, team/player salary, team's league standing, and multiple kills which may impact esports demand.

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