



HAL
open science

Analysis of Enthusiasm Triggers in Competitive Video Games: Overwatch Case Study

Alexis Mortelier, Boris Helleu, Wiem Belhedi, François Rioult

► **To cite this version:**

Alexis Mortelier, Boris Helleu, Wiem Belhedi, François Rioult. Analysis of Enthusiasm Triggers in Competitive Video Games: Overwatch Case Study. International Workshop on Intelligent Technologies for Precision Sports Science 2024 (IT4PSS), Aug 2024, Jeju Island, South Korea. hal-04620944

HAL Id: hal-04620944

<https://hal.science/hal-04620944>

Submitted on 22 Jun 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Analysis of Enthusiasm Triggers in Competitive Video Games: Overwatch Case Study

Alexis Mortelier¹, Boris Helleu², Wiem Belhedi³, François Rioult¹

¹Normandie Univ, UNICAEN, ENSICAEN, CNRS, GREYC, 14000 Caen, France

²NIMEC-UR 969, Université de Caen Basse-Normandie, 14000 Caen, France

³LrSITI, ENIT, Université Tunis El Manar, 1002 Tunis, Tunisie

alexis.mortelier@unicaen.fr

Abstract

We propose a methodology for analyzing viewer engagement during Overwatch League (OWL) broadcasts. On the one hand, we implemented image processing techniques to isolate key visual elements of the spectator interface in OWL videos, enabling an objective and granular analysis of the visual experience, qualified by measures of interest. On the other hand, we extracted audio descriptors from OWL videos of competitive events. We believe these audio descriptors are indicative of the excitement of the crowd and commentators, offering a subjective measure of the impact generated by the video broadcast of the encounter. A *wrapper* approach allowed us to characterize the relevance of the measures of interest by examining their relationship to the hype descriptors.

1 Introduction

Data analysis in the field of video games has become a major area of interest in recent years. The data generated by video games is extremely rich and varied, including information on player behavior, in-game performance, social interactions, preferences and more. This wealth of information offers game developers, researchers and analysts a unique opportunity to better understand game mechanics, optimize the player experience and even detect emerging trends.

One game of particular interest for data analysis is Overwatch. Overwatch is a first-person shooter developed by Blizzard Entertainment, released in 2016. It quickly gained popularity and became a flagship title in the field of competitive shooters. The game stands out for its many characters with unique skills, its various game modes and its well-established competitive aspect.

The consumption of sports entertainment is a complex phenomenon that has given rise to a variety of academic approaches. Sociologists, psychologists, economists and specialists in management and marketing have shed light on a range of seemingly simple questions: why and how do people watch sport? The literature is full of studies analyzing the importance of factors that mobilize fans in the stadium or in front of a screen: the performance of their favorite team, the talent and popularity of the players, the price of tickets,

weather conditions, the atmosphere in the stadium, the design of the equipment, the stakes and the uncertainty of the outcome. These different variables affect spectators differently, depending on their interests and needs, so that there are many different ways of consuming a sporting spectacle.

The study of competitive matches in Overwatch is motivated by the desire to understand and improve the spectator experience. By comparing the spectator interface with the user experience, we aim to determine how what happens on screen can be better understood and appreciated by the audience. To do this, we need to assess the enthusiasm of the crowd and the commentators, and then compare it with what is presented visually.

Analyzing measures of interest in competitive Overwatch matches is then crucial not only for improving the live viewing experience, but also for creating game summaries that captivate and retain viewers, thus contributing to the growth and popularity of e-sports.

2 State of the art

Here, we outline some of the literature on spectator engagement. We then look at Overwatch and his studies, and conclude with a review of studies in the field of crowd clamor analysis.

2.1 Spectator commitment

[Stewart *et al.*, 2003] review the usefulness and diversity of spectator typologies. They show how these models reveal complex fan behaviors, depending on whether they are sensitive to several cognitive and affective factors: emotional connection and identification with a team, search for social interaction or the excitement generated by an event. This makes it difficult to identify the archetypal sports consumer. According to these authors, these typologies enable marketers to refine their strategy, adapt product and pricing, design appropriate equipment, adjust communication campaigns and personalize a consumer experience according to each fan's needs. Essentially, this means understanding fan motivations and behaviors. Daniel C. Funk and Jeff James, at the interface of psychology and marketing, go beyond the notion of satisfying a need to produce theoretical models adapted to sport, such as the Psychological Continuum Model [Funk and James, 2001] or the Fan Attitude Network (FAN) Model [Funk and James, 2004]. So, in

84 the field of traditional sport, the matchday experience is the
85 subject of wide-ranging academic investigation [Meir, 2000;
86 Richards *et al.*, 2022].

87 By mobilizing the interest of numerous fans, sponsors and
88 media around the world, esports has become a scientific ob-
89 ject taken seriously. Indeed, according to Newzoo’s 2022
90 Global Esports & Live Streaming Market Report, the global
91 esports fan audience will reach 640 million by 2025, includ-
92 ing 318 million enthusiastic fans (those who watch this type
93 of content at least once a month). Newzoo estimates that
94 the sector will have generated sales of \$1.38 billion by the
95 end of 2022. So questions about how sports are consumed
96 have found fertile extensions in the esports field. [Hamari and
97 Sjöblom, 2017] are asking what esports is and why it is be-
98 ing watched. According to [Voisin and Besombes, 2023],
99 from practice to mediated spectacle, esports covers a wide
100 spectrum of experiences, so much so that we can speak of es-
101 port audiences. However, the first works dedicated to esports
102 fans favor comparisons with “traditional” sports. In the arti-
103 cle “eSport vs. Sport: A Comparison of Spectator Motives”,
104 [Pizzo *et al.*, 2018] compares spectator motivations for a tra-
105 ditional sport (soccer) and two esports contexts (FIFA Online
106 3 and StarCraft II) in South Korea. The authors listed 15 mo-
107 tivations for attending events (interest, excitement, enjoying
108 players, competitive intensity, meeting people or sharing a
109 moment with family, athletes’ skill, etc.). According to the
110 authors, 11 of the top 15 fan motivations are common to all
111 three events denoting a certain similarity in sports and esports
112 consumption modalities.

113 However, esports has a unique feature. While, like tradi-
114 tional sports, it manages to attract large crowds to stadiums
115 and arenas, it also mobilizes the interest of fans on streaming
116 platforms that enable remote interaction. Numerous studies
117 are therefore focusing on online consumption. [Jang *et al.*,
118 2024] ask: “What makes esports consumers watch streamers’
119 esports live-streaming contents?”. [Qian *et al.*, 2020] have
120 developed the Scale for Esports Spectator Demand (SESD)
121 model, which isolates esports-specific factors: stream qual-
122 ity, chat room, online rewards. While demand for sports en-
123 tertainment is largely explained by the uncertainty of the out-
124 come of a live match, [Wang, 2023] focuses on asynchronous
125 consumption of replays, and on the popularity and skills of
126 players. Skills are particularly valued in FPS games with an
127 assertive technical dimension, while player popularity will be
128 more valued in a MOBA-game¹ that leaves room for enter-
129 tainment and socialization. As stream viewers are themselves
130 fans of videogame competitions, watching the best players is
131 also a way of improving their skills [Hattingh *et al.*, 2024;
132 Qian *et al.*, 2020].

133 More recent contributions attempt to synthesize the exist-
134 ing literature. [Rietz and Hallmann, 2023] have analyzed 25
135 articles dedicated to esports fan behavior. According to their
136 survey, 22 contributions are devoted to online spectators, two
137 to on-site fans and just one compares online/on-site. Back in
138 2016, Taylor noted that at the turn of the 2010s, attendance
139 at esports events evolved from player-spectators to fans. The

¹MOBA stands for Multiplayer Online Battle Arena, such games
in which two teams of heroes battle out to take on an objective.

study conducted by [Jang and Byon, 2020] highlights unique
elements associated with esports events, such as cosplay but
also cheering behaviors, which enrich fans’ experience and
motivate their intention to attend future events.

2.2 e-sport analytics

The e-sport phenomenon has emerged as a new era of
sport, highlighting the opportunities it offers for sports scien-
tists [Himmelstein and Shapiro, 2020]. The way in which tra-
ditional sports and e-sport interact implies that e-sport fits into
the wider landscape of professional sport and can benefit from
the experience and infrastructure of traditional sports [Cas-
tronova, 2020].

Data analysis in e-sport can be used to assess individual
player performance, indeed understanding the specific physi-
cal requirements of games in order to optimize player [Goto
and Rynkiewicz, 2019] is important. This can include mea-
sures such as shot accuracy, responsiveness, reaction times
and so on. By identifying the areas in which a player excels
or struggles, coaches can adapt training to reinforce the nec-
essary skills. For example, a study conducted by [Schulte *et al.*,
2019] showed that the use of biometric data and sensors can
help assess and improve the performance of e-sport play-
ers.

Data analysis can also be used to study the performance of
the team as a whole, as well as that of its opponents. Teams
can examine patterns of play, strategies used by opponents,
and trends in play to adjust their own strategies [Patel and
Lindley, 2020]. For example, research by [Wang *et al.*, 2019]
used data analysis to identify the patterns of play and strate-
gies used by top teams in the Dota 2 game, providing insights
into best practice and possible counter-strategies.

Data analysis in e-sports can involve several methods, ex-
tracting and analyzing data from the games themselves [John-
son, 2020]. This can include data on player actions, match
results [Mortelier and Rioult, 2022], map movements and so
on. Data can be collected using the game API or third-party
software [Drachen *et al.*, 2014]. The specific layout of the
game map affects team strategies and match outcomes, us-
ing game data to identify patterns and trends related to the
map [Reimers and Goldman, 2019].

Analyzing historical match data can provide valuable in-
sights into game trends, player and team performance, strate-
gies used, and so on. For example, [Schubert M., 2010] have
examined user behavior in video games by analyzing histori-
cal game data to understand player preferences.

Game developers can use player data to improve game ex-
perience, game design, and player retention. It could also ad-
dress the methods and tools used in game analytics, as well as
the challenges and opportunities associated with using mas-
sive data from video games [Drachen *et al.*, 2013].

2.3 Overwatch (strategic FPS)

Overwatch is a game in which two teams of six players play
against each other. It is halfway between an FPS (first-person
shooter) and a MOBA. Each player can embody a hero who
can be changed at will during the course of the game.

Heroes have their own specific abilities, as well as an ul-
timate ability that has a major impact on the course of the

197 game. Each hero belongs to a category: tank, support or
 198 damage. The composition of a team is crucial: a team with
 199 heroes with good synergy is vital to the outcome of the game.
 200 Matches are played in 4 different modes: checkpoint, escort,
 201 point attack and hybrid attack/escort. Each game mode places
 202 one team on attack and another on defense, then reverses roles
 203 when the time or objective is reached. When a hero dies, it
 204 takes 10 seconds for him to reappear.

205 Among the few studies on Overwatch, [Tomkinson and Van
 206 Den Ende, 2022] looks at the issue of toxicity in online mul-
 207 tiplayer games, highlighting the strategies put in place by
 208 developers to deal with it. Similarly, [Välisalo and Ruot-
 209 salainen, 2019] look at how players and fans engage with
 210 Overwatch and its nascent esports ecosystem, highlighting the
 211 importance of personality, gender and sexual orientation in
 212 these engagement dynamics. Their study offers a compar-
 213 ative look at how players interact with the game’s playable
 214 characters and with professional esports players, highlight-
 215 ing similarities and emerging differences. Finally, [Vahlo and
 216 Karhulahti, 2022] bring a more quantitative perspective by
 217 using large-scale survey data to map the characteristics of es-
 218 ports players. Their cluster analysis identifies two distinct
 219 profiles of esports players, contributing to our understanding
 220 of the diversity of esports players. These studies underline the
 221 growing importance of Overwatch as an academic research
 222 field, while highlighting the ongoing need to further explore
 223 this game and its impact on video game and esports culture.

224 2.4 Analysis of audio clamor

225 [Proksch *et al.*, 2023] review advances in the acoustic detec-
 226 tion of crowd dynamics, highlighting the use of techniques
 227 such as Fourier analysis, spectroscopy and neural network-
 228 based methods to extract meaningful features from audio
 229 data. [Dosbayev *et al.*, 2021] offer an overview of audio
 230 signal processing methods for detecting abnormal behavior
 231 in crowds, highlighting descriptors such as sound pressure
 232 level and spectral density. [Franzoni *et al.*, 2020] focus on
 233 using audio signals to detect emotions in crowds, exploring
 234 techniques such as vocal intensity analysis and prosody mod-
 235 els. Reviews of [Başbuğ and Sert, 2019; Crocco *et al.*, 2016;
 236 Schuller, 2018; Khalil *et al.*, 2019; Lefèvre *et al.*, 2021;
 237 Rao *et al.*, 2013] provide valuable clues about the use of ad-
 238 vanced techniques such as deep learning and prosodic anal-
 239 ysis to automatically extract complex audio descriptors from
 240 crowd data. This research underlines the growing importance
 241 of audio analysis for detecting abnormal behavior and emo-
 242 tions in crowds.

243 3 Audio analysis of the crowd surge

244 The method we are proposing will enable us to highlight what
 245 arouses the interest and enthusiasm of spectators at official
 246 Overwatch games. As Overwatch does not have a native API
 247 for extracting data, we have developed a video analysis tool.
 248 This is designed to extract relevant information from the spec-
 249 tator overlay present in these videos. The data extracted from
 250 the video is transformed into *interest measures*, while the au-
 251 dio is converted into *audio descriptors* revealing the clamor
 252 of the crowd and the enthusiasm of the commentators. The

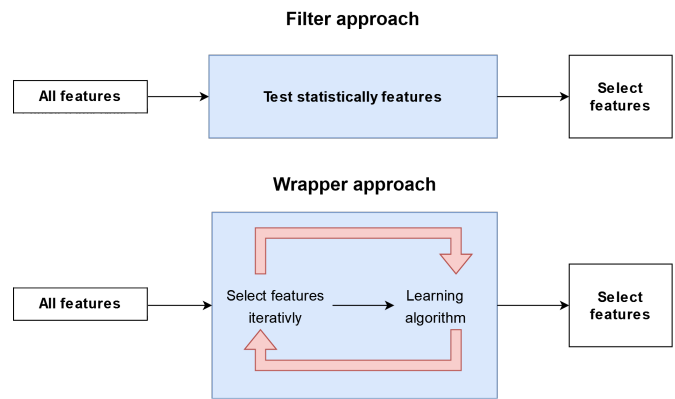


Figure 1: *filter* approach vs. *wrapper*.

253 inclusion of commentators in crowd noise to assess enthusi-
 254 asm in a competitive game is controversial. Commentators
 255 can artificially create an enthusiastic atmosphere to captivate
 256 spectators, which may not accurately reflect the reality of the
 257 game. Their behavior may differ from that of other members
 258 of the crowd. However, they often play a crucial role in am-
 259 plifying key moments and adding context, thus intensifying
 260 the general enthusiasm. Their presence is therefore consid-
 261 ered an integral part of the atmosphere at a competitive event.
 262 Commentators strongly influence spectator perception, their
 263 enthusiasm being contagious and increasing the audience’s
 264 emotional involvement. Ignoring them could give an incom-
 265 plete picture of the enthusiasm generated. Finally, including
 266 commentators helps to capture a more holistic picture of the
 267 sound environment of a competitive game. Moments of sil-
 268 ence, sudden exclamations and crowd interaction add to the
 269 authenticity of the experience.

270 To achieve the highlighting of the enthusiasm, a *wrap-*
 271 *per approach* is employed for assessing every measure’s re-
 272 levancy through the learning of relation with all audio descrip-
 273 tors described in Section 3.3.

274 3.1 Wrapper approach

275 The wrapper approach [Kohavi and John, 1998] is originally
 276 an *attribute selection* technique that pronounces on the rele-
 277 vance of descriptors by examining the training performance
 278 of a predictive system. Indeed, a distinction is made between
 279 the *filter* [Germano, 1992] approach, which examines the sta-
 280 tistical characteristics of attributes (such as correlation coef-
 281 ficients) to choose among them, and the *wrapper* approach,
 282 which iteratively selects attributes that induce good perfor-
 283 mance from the learning algorithm employed (see Figure 1).

284 The *wrapper* approach thus performs a search in the space
 285 of attribute subsets, guided by the performance of the learn-
 286 ing algorithm. The evaluation criterion is simply the learning
 287 performance. The *wrapper* approach enables finer selection
 288 than the *filter* approach, but at the cost of a longer computa-
 289 tion time. We use it here as a feature importance method.

290 3.2 Data acquisition - Analysis of transcript 291 images

292 Overwatch has no native API allowing users to extract data

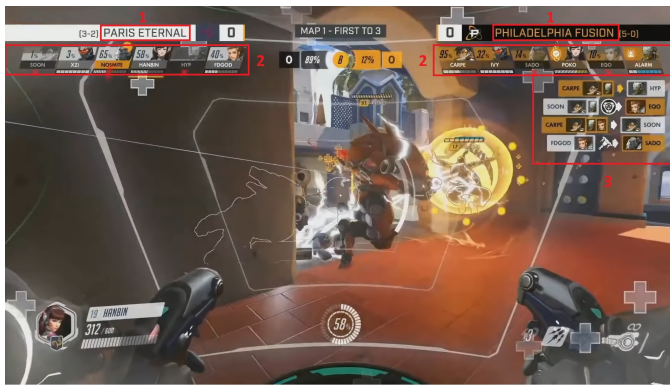


Figure 2: An image from the transcription of a match of Overwatch.

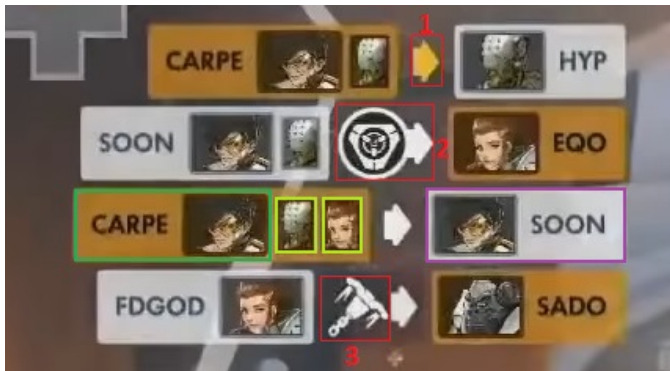


Figure 3: An image of the killfeed from Overwatch.

and the player’s nickname associated with this hero are displayed in Zone 2 (see Figure 4). In Zone 3, the killfeed (see Figure 3) shows the last six kills and/or destructions, with the most recent at the top. Both names are given the color appropriate to the team, and a player hero icon is placed next to them (boxed in green). The hero icons of players taking part in the kill are displayed next to them (boxed in yellow). The white arrow indicates the direction of the kill; if it is colored, it is a critical kill (Zone 1); if it is an ability (Zone 3) or an ultimate ability (Zone 2) that kills, the ability logo is shown next to it.

Each game video is then subjected to an analysis of the extracted data, beginning with the evaluation of specific measures for each category : damage suffered (in DPS), healing received (in HPS), ultimate ability status, ultimate ability use, hero death. The events of death and use of ultimate abilities are extended over 10 seconds (corresponding to the reappear-ance time) for each successive use or death. Each player’s individual interest in each category is then aggregated to create a category interest.

3.3 Audio descriptor extraction

Audio analysis is useful for understanding the emotional and dynamic aspects of live events, such as Overwatch matches. For this task, a set of audio descriptors were extracted using Librosa, a Python library specialized in audio signal processing [McFee *et al.*, 2015]. These descriptors, selected for their ability to capture different aspects of the soundscape, offer a rich perspective on the variations in crowd excitement and commentator enthusiasm throughout the match.

Firstly, MFCC coefficients (*Mel-Frequency Cepstral Coefficients*) are used to represent the spectral shape of the audio signal [Davis and Mermelstein, 1980]. These coefficients, often used in speech recognition, capture frequency characteristics at different time scales. In the context of football matches, variations in MFCCs can reveal fluctuations in crowd mood and commentator excitement at key moments of the game.

STFT chroma (*Short-Time Fourier Transform*) is then used to analyze the energy distribution of harmonic components in different pitch classes, providing information on tonality and tonal variations in the audio [Fujishima, 1999]. This measurement can be linked to background music or sounds characteristic of in-game actions, enriching the analysis of the overall soundscape.

The spectral centroid, which indicates the center of gravity of frequencies in the audio signal, can reveal information about the brightness of the sound. High values of this measure can indicate an increased presence of high-pitched sounds, such as those produced by screams or applause in a stadium during moments of high intensity.

Spectral bandwidth and spectral contrast respectively provide information about the variety of frequencies present in the audio and sudden changes in the sound texture [Peeters, 2003; Baer *et al.*, 1993]. These measures can be used to detect moments of intense excitement or relative calm during the match.

Zero crossing rate and onset strength are used to assess the amount of variation and the presence of transients in the au-

293 directly from a current match or recent game. Fortunately,
 294 many Overwatch matches are recorded and uploaded to video
 295 platforms such as YouTube. These videos contain game
 296 footage captured with the spectator interface (Figure 2),
 297 which offers an overview of the match and the various player
 298 actions: damage inflicted, healing provided, death events, ul-
 299 timate ability status, ultimate ability usage. This overlay pro-
 300 vides *objective* information on the state of the match.

301 To exploit this data present in videos, we have developed a
 302 specialized replay visualization tool². This tool is designed to
 303 extract relevant information from the viewer overlay. Thanks
 304 to image analysis techniques (OCR, feature matching, pattern
 305 matching, erosion and dilation), this information can be cap-
 306 tured from the spectator interface, providing a precise status
 307 of the game.

308 For example, Zone 1 on Figure 2 shows the names of the two teams and the score. The team compositions, each
 309 player’s hero, the hero’s life, the state of his ultimate ability
 310

²<https://github.com/Nikkunemufr/Python/tree/master/MetaWatch>

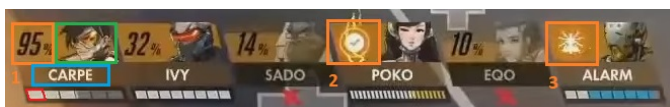


Figure 4: Team hero banner (zone 2 on the right of Figure 2).

369 dio signal [Gouyon *et al.*, 2000] [Bello *et al.*, 2005]. These
 370 aspects are essential for understanding the percussive or sonic
 371 character of audio, highlighting moments of action or strong
 372 emotion.

373 Tempo, power spectrogram, pitch and energy are also
 374 key descriptors used to capture the perceived rhythm, over-
 375 all intensity and pitch of sounds in audio [Dixon, 2001;
 376 Klapuri, 2004; Ghaemmaghami *et al.*, 1997; Ramirez *et al.*,
 377 2004]. These measures can be used to highlight moments
 378 of crowd excitement, commentator enthusiasm and other as-
 379 pects of the game’s soundscape, providing a rich and compre-
 380 hensive analysis of live events.

381 The use of these varied audio descriptors enables an in-
 382 depth and nuanced analysis of the soundscape of *Overwatch*
 383 matches, providing information on crowd excitement, com-
 384 mentator enthusiasm and other emotional aspects of the game
 385 in real time.

386 4 Experiments

387 4.1 Dataset

388 We processed data from 14 *Overwatch* matches, giving rise
 389 to sixty different maps (i.e. games), for a total duration of
 390 twenty hours of video. This extraction yielded 60 sequences
 391 ranging in size from 900 to 1 800 one-second time steps.
 392 For each time step of these sequences, descriptors of interest
 393 are obtained on damage (*damage*), healing (*heal*), death
 394 (*death*), loading of ultimate abilities (*state of ulti*),
 395 use of ultimate abilities (*use of ulti*) as well as descrip-
 396 tors from the audio tape of the transcripts.

397 4.2 Model structure

398 The *wrapper* approach was implemented as follows: as many
 399 models as there are descriptors combinations are trained in re-
 400 gression to predict the audio descriptors. The training perfor-
 401 mance (Mean Squared Error – MSE, and number of epochs
 402 for convergence) of the model was evaluated to determine the
 403 relevance of each descriptor combination for learning all the
 404 audio descriptors.

405 The trained model was a gated recurrent neural network
 406 (GRU) rather than a Long Short-Term Memory (LSTM) for
 407 several reasons. Firstly, there is no long-term time depen-
 408 dency (a strength of LSTMs) which is critical to this specific
 409 task. Unlike LSTMs, GRUs are designed to capture short-
 410 and medium-term temporal dependencies. This simplifica-
 411 tion reduces the complexity of the model, which can help it
 412 to converge faster and train more efficiently.

413 4.3 Results

414 Table 1 shows the different combinations of measures and
 415 their performance for audio descriptor prediction, measured
 416 with MSE. For each descriptor, Table 2 shows the average
 417 MSE for the models trained *without* a combination including
 418 that descriptor, the average MSE *with* that descriptor, and fi-
 419 nally the percentage improvement (remember that the lower
 420 the MSE, the better it is). The *improvement* column of the Ta-
 421 ble 2 therefore provides an indication of the relevance of each
 422 descriptor for the MSE. A positive value suggests that the

heal	damage	use of ulti	state of ulti	death	MSE
×	×	×	×	×	0.351
	×	×	×	×	0.352
×	×		×	×	0.355
×	×		×		0.356
×	×	×	×		0.357
×		×	×	×	0.357
×			×	×	0.361
					0.363
	×	×	×		0.365
	×		×		0.365
×	×	×			0.365
×	×	×		×	0.366
×			×	×	0.367
×		×		×	0.367
	×	×			0.374
×		×			0.375
×	×			×	0.394
	×	×		×	0.439
	×		×	×	0.441
	×	×	×		0.444
×	×				0.456
	×			×	0.468
×				×	0.478
×	×				0.521
					0.534
		×		×	0.710
			×	×	0.793
		×	×	×	0.793
				×	0.819
			×		0.872
		×			0.880
		×	×		0.881

Table 1: MSE for each descriptor combination.

measure	without (MSE)	with (MSE)	improvement (%)
heal	0.55	0.38	31.4
damage	0.53	0.39	26.2
use of ulti	0.45	0.45	-1.8
state of ulti	0.44	0.46	-6.2
death	0.43	0.47	-9.5

Table 2: Contribution of each descriptor to the MSE.

423 presence of the measure improves model convergence, while
424 a negative value indicates a deterioration in prediction.

425 Analyzing the results, we observe that for the heal and
426 damage measures, their inclusion improves prediction accu-
427 racy (reduced MSE). This suggests that these measures pro-
428 vide important information for the model, making it easier to
429 learn and improving its predictive performance.

430 On the other hand, the inclusion of ultimate ability state
431 and death events leads to a degradation of the MSE. This may
432 indicate that these measures introduce noise or information ir-
433 relevant to the prediction task, disrupting the learning process
434 and reducing prediction accuracy.

435 Analysis of this table suggests that not all measures con-
436 tribute equally to improving model performance. Some indi-
437 cators appear to be more relevant than others, underlining the
438 importance of carefully selecting the features to be included
439 in the learning process to obtain the best results.

440 5 Conclusion

441 We proposed a method for analyzing spectator engagement
442 in Overwatch League broadcasts, examining the impact on
443 crowd engagement of information provided by the game. The
444 results show that heal and damage indicators significantly im-
445 proved the performance of the crowd engagement prediction
446 model, while features relating to ultimate abilities disrupted
447 the learning process.

448 This study highlights the importance of the relevance of
449 the data used to analyze spectator engagement. Identifying
450 the most significant indicators is a step towards understanding
451 and improving the spectator experience.

452 Acknowledgements

453 The research described here is supported by the French Na-
454 tional Research Agency (ANR) and Region Normandie under
455 grant HAISCoDe

456 References

- 457 [Baer *et al.*, 1993] Thomas Baer, Brian CJ Moore, and Stu-
458 art Gatehouse. Spectral contrast enhancement of speech in
459 noise for listeners with sensorineural hearing impairment:
460 Effects on intelligibility, quality, and response times. vol-
461 ume 30, pages 49–49. Citeseer, 1993.
- 462 [Başbuğ and Sert, 2019] Ahmet Melih Başbuğ and Mustafa
463 Sert. Analysis of deep neural network models for acoustic
464 scene classification. pages 1–4, 2019.
- 465 [Bello *et al.*, 2005] Juan Pablo Bello, Laurent Daudet, Samer
466 Abdallah, Chris Duxbury, Mike Davies, and Mark B Sandler.
467 A tutorial on onset detection in music signals. vol-
468 ume 13, pages 1035–1047. IEEE, 2005.
- 469 [Castronova, 2020] Edward Castronova. The surprising im-
470 pact of professional sports on esports. *Journal of Sports*
471 *Economics*, 21(7):705–717, 2020.
- 472 [Crocco *et al.*, 2016] Marco Crocco, Marco Cristani, Andrea
473 Trucco, and Vittorio Murino. Audio surveillance: A
474 systematic review. *ACM Computing Surveys (CSUR)*,
475 48(4):1–46, 2016.

- [Davis and Mermelstein, 1980] Stephen Davis and Paul 476
Mermelstein. Mel frequency cepstral coefficients (mfccs). 477
In *Speech and Audio Signal Processing*, 1980. 478
- [Dixon, 2001] Simon Dixon. Automatic tempo and beat 479
analysis of acoustic musical signals. In *Journal of New* 480
Music Research, volume 30, pages 39–58, 2001. 481
- [Dosbayev *et al.*, 2021] Zhandos Dosbayev, Rustam Ab- 482
drakhmanov, Oxana Akhmetova, Marat Nurtas, Zhalgas- 483
bek Iztayev, Lyazzat Zhaidakbaeva, and Lazzat Shaimer- 484
denova. Audio surveillance: detection of audio-based 485
emergency situations. pages 413–424, 2021. 486
- [Drachen *et al.*, 2013] Anders Drachen, Magy Seif El-Nasr, 487
and Alessandro Canossa. *Game analytics: maximizing the* 488
value of player data. Springer, 2013. 489
- [Drachen *et al.*, 2014] Anders Drachen, Matthew Yancey, 490
John Maguire, Derrek Chu, Iris Yuhui Wang, Tobias 491
Mahlmann, Matthias Schubert, and Diego Klabajan. Skill- 492
based differences in spatio-temporal team behaviour in de- 493
fence of the ancients 2 (DotA 2). In *2014 IEEE Games* 494
Media Entertainment, pages 1–8. IEEE, 2014. 495
- [Franzoni *et al.*, 2020] Valentina Franzoni, Giulio Biondi, 496
and Alfredo Milani. Emotional sounds of crowds: 497
spectrogram-based analysis using deep learning. *Multi-* 498
media tools and applications, 79(47):36063–36075, 2020. 499
- [Fujishima, 1999] T. Fujishima. Chroma feature analysis and 500
synthesis. In *Proceedings of the International Computer* 501
Music Conference, 1999. 502
- [Funk and James, 2001] D.C. Funk and J.D. James. The psy- 503
chological continuum model: A conceptual framework for 504
understanding an individual’s psychological connection to 505
sport. *Sport Management Review*, 4:119–150, 2001. 506
- [Funk and James, 2004] Daniel C. Funk and Jeffrey D. 507
James. The fan attitude network (FAN) model: Explor- 508
ing attitude formation and change among sport consumers. 509
Sport Management Review, 7(1):1–26, May 2004. 510
- [Germano, 1992] Massimo Germano. Turbulence: the filter- 511
ing approach. *Journal of Fluid Mechanics*, 238:325–336, 512
1992. 513
- [Ghaemmaghami *et al.*, 1997] S Ghaemmaghami, Mohamed 514
Deriche, and Boualem Boashash. A new approach to pitch 515
and voicing detection through spectrum periodicity mea- 516
surement. 2:743–746, 1997. 517
- [Goto and Rynkiewicz, 2019] Masanori Goto and Joseph 518
Rynkiewicz. Performance indicators and team styles in 519
DotA 2. *International Journal of Performance Analysis in* 520
Sport, 19(6):1120–1131, 2019. 521
- [Gouyon *et al.*, 2000] Fabien Gouyon, François Pachet, 522
Olivier Delerue, et al. On the use of zero-crossing rate for 523
an application of classification of percussive sounds. In 524
Proceedings of the COST G-6 conference on Digital Au- 525
dio Effects (DAFX-00), Verona, Italy, volume 5, page 16, 526
2000. 527
- [Hamari and Sjöblom, 2017] J. Hamari and M. Sjöblom. 528
What is esports and why do people watch it? *Internet* 529
Research, 27(2):211–232, 2017. 530

- 531 [Hattingh *et al.*, 2024] W. Hattingh, L. Van den Berg, and
532 A. Bevan-Dye. The “why” behind generation y ama-
533 teur gamers’ ongoing esports gameplay intentions. *In-*
534 *ternational Journal of Sports Marketing and Sponsorship*,
535 25(1):67–87, 2024.
- 536 [Himmelstein and Shapiro, 2020] Matthew Himmelstein
537 and Joshua Shapiro. Esports: A new era of sport with
538 opportunities for sports scientists. *International Journal*
539 *of Sports Physiology and Performance*, 15(4):485–487,
540 2020.
- 541 [Jang and Byon, 2020] W.W. Jang and K.K. Byon. An-
542 tecedents and consequence associated with esports game-
543 play. *International Journal of Sports Marketing and Spon-*
544 *sorship*, 21(1):1–22, 2020.
- 545 [Jang *et al.*, 2024] W.W. Jang, W. Choi, M.J. Kim, H. Song,
546 and K.K. Byon. What makes esports consumers watch
547 streamers’ esports live-streaming contents? extending the
548 theory of planned behavior. *International Journal of*
549 *Sports Marketing and Sponsorship*, 25(2):288–309, 2024.
- 550 [Johnson, 2020] Todd P Johnson. An introduction to esports
551 data analytics. In *E-Sports Performance and Analytics*,
552 pages 1–21. Springer, Cham, 2020.
- 553 [Khalil *et al.*, 2019] Ruhul Amin Khalil, Edward Jones, Mo-
554 hammad Inayatullah Babar, Tariqullah Jan, Moham-
555 mad Haseeb Zafar, and Thamer Alhussain. Speech emo-
556 tion recognition using deep learning techniques: A review.
557 *IEEE access*, 7:117327–117345, 2019.
- 558 [Klapuri, 2004] Anssi Klapuri. Signal processing methods
559 for the automatic transcription of music. Tampere Univer-
560 sity of Technology Finland, 2004.
- 561 [Kohavi and John, 1998] Ron Kohavi and George H John.
562 The wrapper approach. In *Feature extraction, construc-*
563 *tion and selection*, pages 33–50. Springer, 1998.
- 564 [Lefèvre *et al.*, 2021] Bruno Lefèvre, Rachit Agarwal,
565 Valérie Issarny, and Vivien Mallet. Mobile crowd-sensing
566 as a resource for contextualized urban public policies:
567 a study using three use cases on noise and soundscape
568 monitoring. *Cities & Health*, 5(1-2):179–197, 2021.
- 569 [McFee *et al.*, 2015] Brian McFee, Colin Raffel, Dawen
570 Liang, Daniel PW Ellis, Matt McVicar, Eric Battenberg,
571 and Oriol Nieto. librosa: Audio and music signal analysis
572 in python., 2015.
- 573 [Meir, 2000] R. Meir. Fan reaction to the match day expe-
574 rience: A case study in english professional rugby league
575 football. *Sport Marketing Quarterly*, 9(1):34–42, 2000.
- 576 [Mortelier and Rioult, 2022] Alexis Mortelier and François
577 Rioult. Addressing the complexity of MOBA games
578 through simple geometric clues. In *International Con-*
579 *ference on Computational Collective Intelligence*, pages
580 643–649. Springer, 2022.
- 581 [Patel and Lindley, 2020] Tirth Patel and Samuel Lindley.
582 Analyzing physical exertion in esports: A review. *Enter-*
583 *tainment Computing*, 34:100387, 2020.
- 584 [Peeters, 2003] Geoffroy Peeters. Measuring the timbre of
585 audio signals. In *Proceedings of the ISMIR*, 2003.
- [Pizzo *et al.*, 2018] A.D. Pizzo, N. Sangwon, B.J. Baker, 586
L. Mi Ae, K. Doohan, and D.C. Funk. esports vs. sport: A 587
comparison of spectator motives. *Sport Marketing Quar-* 588
terly, 27(2):108–123, 2018. 589
- [Proksch *et al.*, 2023] Shannon Proksch, Majerle Reeves, 590
Kent Gee, Mark Transtrum, Chris Kello, and Ramesh 591
Balasubramaniam. Recurrence quantification analy- 592
sis of crowd sound dynamics. *Cognitive Science*, 593
47(10):e13363, 2023. 594
- [Qian *et al.*, 2020] T. Y. Qian, J. J. Zhang, J. J. Wang, 595
and J. Hulland. Beyond the game: Dimensions of es- 596
ports online spectator demand. *Communication & Sport*, 597
8(6):825–851, 2020. 598
- [Ramirez *et al.*, 2004] Javier Ramirez, José C Segura, Car- 599
men Benitez, Angel De La Torre, and Antonio Rubio. Ef- 600
ficient voice activity detection algorithms using long-term 601
speech information. volume 42, pages 271–287. Elsevier, 602
2004. 603
- [Rao *et al.*, 2013] K Sreenivasa Rao, Shashidhar G 604
Koolagudi, and Ramu Reddy Vempada. Emotion 605
recognition from speech using global and local prosodic 606
features. *International journal of speech technology*, 607
16:143–160, 2013. 608
- [Reimers and Goldman, 2019] Victor Reimers and Josiah 609
Goldman. League of legends: The influence of the map on 610
performance in esports. In *Proceedings of the 24th ACM* 611
SIGKDD International Conference on Knowledge Discov- 612
ery & Data Mining, pages 2658–2666, 2019. 613
- [Richards *et al.*, 2022] Jessica Richards, Daniela Spanjaard, 614
Michelle O’Shea, and Francine Garlin. The changing 615
carnival: reimaging and recreating the match-day expe- 616
rience in multi-purpose stadiums. *Journal of Sport &* 617
Tourism, 26(3):269–284, 2022. 618
- [Rietz and Hallmann, 2023] J. Rietz and K. Hallmann. A 619
systematic review on spectator behavior in esports: why 620
do people watch? *International Journal of Sports Market-* 621
ing and Sponsorship, 24(1):38–55, 2023. 622
- [Schubert M., 2010] Lischke L. Schubert M. User behavior 623
in games. *Entertainment Computing-ICEC*, 2010. 624
- [Schuller, 2018] B. W. Schuller. Automatic emotion recog- 625
nition from speech: A review of the literature and recom- 626
mendations for practical realization. *Speech Communica-* 627
tion, 99:102–128, 2018. 628
- [Schulte *et al.*, 2019] Simon Schulte, Joakim Ostlund, An- 629
ders Fagergren, Mikael Thorén, and Daniel Pargman. Ex- 630
ploring biometric data acquisition and analysis in esports. 631
In *2019 IEEE Conference on Games (CoG)*, pages 1–8. 632
IEEE, 2019. 633
- [Stewart *et al.*, 2003] B. Stewart, A.C.T. Smith, and 634
M. Nicholson. Sport consumer typologies: A critical 635
review. *Sport Marketing Quarterly*, 12(4):206–216, 2003. 636
- [Tomkinson and Van Den Ende, 2022] Simon Tomkinson 637
and Benjamin Van Den Ende. ‘thank you for your 638
compliance’: Overwatch as a disciplinary system. *Games* 639
and culture, 17(2):198–218, 2022. 640

- 641 [Vahlo and Karhulahti, 2022] Jarno Vahlo and Veli-Matti
642 Karhulahti. Two Overwatch player profiles. In *Modes of*
643 *esports engagement in Overwatch*, pages 11–30. Springer,
644 2022.
- 645 [Voisin and Besombes, 2023] Nicolas Voisin and Nicolas
646 Besombes. Esport. *Publictionnaire. Dictionnaire ency-*
647 *clopédique et critique des publics*, 2023.
- 648 [Välisalo and Ruotsalainen, 2019] Tero Välisalo and Mikko
649 Ruotsalainen. "I never gave up" engagement with playable
650 characters and esports players of overwatch. In *Proceed-*
651 *ings of the 14th International Conference on the Founda-*
652 *tions of Digital Games*, pages 1–6, August 2019.
- 653 [Wang *et al.*, 2019] Peng Wang, Qing Song, Xiaohua Lin,
654 and Yichao Lu. An analysis on strategy evolution in DotA
655 2. In *Proceedings of the 10th International Conference on*
656 *Internet Multimedia Computing and Service*, pages 46–50,
657 2019.
- 658 [Wang, 2023] W. Wang. Returning for skill or popularity?
659 the demand for esports match replay. *International Jour-*
660 *nal of Sports Marketing and Sponsorship*, 24(2):295–310,
661 2023.