

# Mining Insights from Esports Game Reviews with an Aspect-Based Sentiment Analysis Framework

Akula Tarun Sai, Sripada Nihar, Lakkadasu Pradeep Kumar, T Rama Krishna\*

Department of Information Technology, Guru Nanak Institutions Technical Campus, Hyderabad.

\*Assistant Professor, Department of IT, Guru Nanak Institutions Technical Campus, Hyderabad.

**Abstract:** The explosive growth of player-versus-player games and tournaments has catapulted esports games into a rapidly expanding force in the gaming industry. However, novice and armature players' voices are often inadvertently overlooked because of a lack of effective analytical methods, despite the close collaboration between professional esports teams and operators. To ensure the quality of esports game services and establish a balanced gaming environment, it is essential to consider the opinions of unprofessional players and comprehensively analyze their reviews. This study proposes a new framework for analyzing esports reviews of players. It incorporates two key components: topic modeling and sentiment analysis. Utilizing the Latent Dirichlet Allocation (LDA) algorithm, the framework effectively identifies diverse topics within reviews. These identified topics were subsequently employed in a prevalence analysis to uncover the associations between players' concerns and various esports games. Moreover, it leverages cutting-edge Bidirectional Encoder Representations from Transformers (BERT) in conjunction with a Transformer (TFM) downstream layer, enabling accurate detection of players' sentiments toward different topics. We experimented using a dataset containing 1.6 million English reviews collected up to December 2021 for four esports games on Steam: TEKKEN7, Dota2, PUBG, and CS:GO. The experimental results demonstrated that the proposed framework can efficiently identify players' concerns and reveal interesting keywords underlying their reviews. Consequently, it provides precise insights and valuable customer feedback to esports game operators, enabling them to enhance their services and provide an improved gaming experience for all players.

Keywords: Esports, topic modeling, prevalence analysis, sentiment analysis, steam.

## 1. INTRODUCTION

Esports is a rapidly growing industry that supports over two billion players and spectators worldwide, creating a billion-dollar revenue market annually. The competitive characteristics of esports have attracted interest from players, as these games emphasize Player versus Player (PvP) rather than just graphics and storylines. This makes it more enjoyable to watch competition. Recently, esports were debuted as an official medal sport in the 2022 Asian Games. Esports games can be classified into several groups: firstperson shooter (FPS), battle royales (BR), multiplayer online battle arena (MOBA), real-time strategy (RTS), fighting, and card games.

According to the global esports market investigation by Newzoo, for the top 25 live esports games watched on YouTube, Twitch, and Mixer, 72% of the games consist of FPS, BR, MOBA, and Fighting. These games are typically much more hardcore because of their competitive elements. By analyzing over 100 million users on Steam, Baumann et al. demonstrated that hardcore gamers can be grouped into separate clusters, such as which match our observation with features of esports games. As new games are released for desktop gaming clients, such as Steam, Origin, Uplay, and Battle.net, these clients have developed rapidly in recent years. They allow players to purchase and enjoy one-stop gaming services. Future updates can be easily made, eliminating players needing to find download paths and update the games themselves. With the development of clients, gaming communities have grown gradually, generating forums such as Steam, Ubisoft, Origin, and IGN.

Steam is the ultimate destination for playing, discussing, and creating games among these platforms, containing nearly 30,000 games, from AAA publishers to mid-sized or major publishers. Steam has a large community with over 100 million potential players and provides a comprehensive and large-scale review system. Several previous studies collected data from Steam to analyze player behavior. In the digital transformation era, data can easily be collected from various sources in diverse formats, with text being one of the most common unstructured data types. However, traditional technologies have become unable to handle such massive and unstructured data, leading to the emergence of big data in text classification, cutting-edge machine learning, and deep learning techniques that can perform highly accurate lower-level engineering and computation functions. Text classification is at the heart of various software systems that process textual data on a large scale. It performs fundamental natural language processing (NLP) tasks and is broadly applied for sentiment analysis, spam detection, and topic labeling. Sentiment analysis is an important topic in NLP.

It aims to systematically and automatically analyze the opinions and emotions contained in text. Sentiment analysis classification algorithms can detect positive or negative sentiments in a text at different levels, such as document, sentence, and aspect levels. Users may have different granularities in interesting aspects. Thus, aspect-based sentiment analysis (ABSA) is more sophisticated in reflecting users' detailed opinions and sentiments. An ABSA task involves two essential subtasks: aspect term extraction (ATE), which involves identifying the aspects of interest, and aspect sentiment classification (ASC), which involves determining the polarity of identified aspects. Conducted a study on Steam reviews and found that game reviews have unique characteristics compared with other types of reviews. However, the analysis of game reviews presents several challenges. First, Steam game reviews use the "Recommended" or "Not Recommended" system instead of a rating system on a scale of 1 to 5. This system may not always accurately reflect the author's attitude because of the possibility of incorrect selection.

Second, Game reviews are often unhelpful, with identifying that 58% of reviews fall into the "Not Helpful" category. This makes it difficult to find informative reviews without the help of analytical tools. Valuable game reviews can typically be summarized into categories, such as Pros, Cons, Bugs, Suggestions, and Videos. Thus, using ABSA can be useful in reducing the workload and enabling esports operators to grasp key information quickly and accurately. Recently, the attention of many researchers has been drawn to sentiment analysis of game clients. Game reviews on game clients serve as valuable resources to reflect esports enthusiasts' preferences and existing problems, allowing operators to enhance the quality of an esports game. For instance, showed that the imbalances between players of different ranks resulting from the services offered by esports operators can cause a massive loss of noob players. Conversely, such imbalances can make the game too easy, which contradicts the nature of esports games. Professional and noob esports players are the two ends of a scale and both are critical to the future of an esports game. However, esports operators prioritize professional players' opinions when serving these two groups, often ignoring large but silent noob players. These observations motivated the design of an approach to help esports game operators to gain more accurate information and feedback from the enormous number of middle/low-ranked players to enhance their services.

## II.RELATED WORKS

They extracted features from tweets using word2vec before feeding them to the classifier. The authors found that the use of word2vec in feature extraction improves the accuracy of the model substantially. Sulaiman et al. [12] presented a deep neural network based approach for sentiment analysis of tweets. They used a convolutional neural network (CNN) model and evaluated the model with two different datasets. Experimental results showed that the proposed method outperforms other baseline methods such as Naive Bayes.

This section provides a representative set of studies related twitter sentiment analysis in various domains. Bhayani and Huang [2] categorized the collected tweets into negative or positive sentiment. They collect training data-set automatically from Twitter. Pak and Paroubek [3] identified the use of creative language and made automatic sentiment analysis of tweets. The authors used hashtags to build their classifier. They utilize corpus of Edinburgh Twitter to create hashtags that have most frequent keywords. These hashtags are classified manually and are used to classify the tweets. They used ngrams and Part of Speech (PoS) features. They achieved the best results with n-gram features. The use of part-of-speech features caused a drop in overall accuracy.

The aim of our work is to build a sentiment analyzer model that can detect sentiment, so that we can apply this model to real tweets collected from different airlines in the Gulf region and compare/analyses them to see public sentiments towards the selected airlines. As a result, the size of data is increasing enormously and creating opportunities for researchers to use these networks as sources for data mining. Small messages in Twitter are used to share opinions and sentiments that people have about products, brands, or events. These sentiments are broadly categorized as positive, negative or neutral. Traders are using powerful computers to get information from news reports, company Web sites, blog posts and even Twitter messages and then analyzing these data to decide what it all means for the markets. Markets often move based on human emotion and thus peoples' sentiments may provide a useful signal for trading.

The explosive growth of player-versus-player games and tournaments has catapulted esports games into a rapidly expanding force in the gaming industry. However, novice and armature players' voices are often inadvertently overlooked because of a lack of effective analytical methods, despite the close collaboration between professional esports teams and operators. To ensure the quality of esports game services and establish a balanced gaming environment, it is essential to consider the opinions of unprofessional players and comprehensively analyze their reviews.

- A linguistic analysis technique that determines the emotional state of the text of positive or negative emotion is part of the NLP.
- The popularity of these platforms such as Twitter, Face book, and YouTube has increased rapidly with the rapid development in these services.
- Markets often move based on human emotion and thus peoples' sentiments may provide a useful signal for trading.

### III. LITERATURE SURVEY

A. Go, R. Bhayani, and L. Huang, we introduce a novel approach for automatically classifying the sentiment of Twitter messages. These messages are classified as either positive or negative with respect to a query term. This is useful for consumers who want to research the sentiment of products before purchase, or companies that want to monitor the public sentiment of their brands. There is no previous research on classifying sentiment of messages on microblogging services like Twitter. We present the results of machine learning algorithms for classifying the sentiment of Twitter messages using distant supervision. Our training data consists of Twitter messages with emoticons, which are used as noisy labels. This type of training data is abundantly available and can be obtained through automated means. We show that machine learning algorithms (Naive Bayes, Maximum Entropy, and SVM) have accuracy above 80% when trained with emoticon data. This paper also describes the preprocessing steps needed in order to achieve high accuracy. The main contribution of this paper is the idea of using tweets with emoticons for distant supervised learning.

A. Pak and P. Paroubek, microblogging today has become a very popular communication tool among Internet users. Millions of users share opinions on different aspects of life every day. Therefore microblogging web-sites are rich sources of data for opinion mining and sentiment analysis. Because microblogging has appeared relatively recently,

there are a few research works that were devoted to this topic. In our paper, we focus on using Twitter, the most popular microblogging platform, for the task of sentiment analysis. We show how to automatically collect a corpus for sentiment analysis and opinion mining purposes. We perform linguistic analysis of the collected corpus and explain discovered phenomena. Using the corpus, we build a sentiment classifier that is able to determine positive, negative and neutral sentiments for a document. Experimental evaluations show that our proposed techniques are efficient and performs better than previously proposed methods. In our research, we worked with English, however, the proposed technique can be used with any other language.

H. Saif, Y. He, and H. Alani, sentiment analysis is one of the new challenges appeared in automatic language processing with the advent of social networks. Taking advantage of the amount of information is now available, research and industry have sought ways to automatically analyze sentiments and user opinions expressed in social networks. In this paper, we place ourselves in a difficult context, on the sentiments that could thinking of suicide. In particular, we propose to address the lack of terminological resources related to suicide by a method of constructing a vocabulary associated with suicide. We then propose, for a better analysis, to investigate Weka as a tool of data mining based on machine learning algorithms that can extract useful information from Twitter data collected by Twitter4J. Therefore, an algorithm of computing semantic analysis between tweets in training set and tweets in data set based on WordNet is proposed. Experimental results demonstrate that our method based on machine learning algorithms and semantic sentiment analysis can extract predictions of suicidal ideation using Twitter Data. In addition, this work verify the effectiveness of performance in term of accuracy and precision on semantic sentiment analysis that could thinking of suicide.

A. G. Mauri and R. Minazzi, the objective of the paper is to study the impact that hotel guests reviews posted on consumer-generated websites have on the consumer decision-making process and service expectations. An experimental study has been conducted to test the hypotheses and the research question. 349 young adults were involved in an online survey that asked to imagine searching for a hotel and reading other customers' reviews of a hypothetical chosen hotel. Three scenarios were created by studying a few comments posted by customers on the main websites used by tourists. Results show a positive correlation between both hotel purchasing intention and expectations of the customers and valence of the review. On the contrary, the presence of hotel managers' responses to guests' reviews has a negative impact on purchasing intentions. The study enriches the stream of research on word-of-mouth in the hospitality industry and analyses a new operational problem for lodging managers. Hotels should reply to online customer reviews or not?

Y. Tong, B. Zhou, and J. Huang, twitter sentiment analysis model trained from data of one topic may performs worse on another topic. While tweets have diverse topics, and the topic of target data of sentiment analysis task is change with the application requirement, which makes it hard to get a good performance. We also notice that one model cannot performs well on every topic, and tweets have no sentiment label to train the model. On the other hand, there are plenty of available text data with sentiment label and topic information such as online movie and product reviews. So we propose a method based on transfer learning, which use topic information and term distribution as a bridge between target tweets and texts from other sources. It could quickly find appropriate in-stances from other sources, and then use them to train a model adapting to target tweets of specific topic for getting better performance. The experiment result shows the effectiveness of the proposed method.

A. Ahmed and D. Elise, sentiment analysis on social media such as Twitter has become a very important and challenging task. Due to the characteristics of such data tweet length, spelling errors, abbreviations, and special characters—the sentiment analysis task in such an environment requires a non-traditional approach. Moreover, social media sentiment analysis is a fundamental problem with many interesting applications. Most current social media sentiment classification methods judge the sentiment polarity primarily according to textual content and neglect other

information on these platforms. In this paper, we propose a neural network model that also incorporates user behavioral information within a given document (tweet). The neural network used in this paper is a Convolutional Neural Network (CNN). The system is evaluated on two datasets provided by the SemEval-2016 Workshop. The proposed model outperforms current baseline models (including Naive Bayes and Support Vector Machines), which shows that going beyond the content of a document (tweet) is beneficial in sentiment classification, because it provides the classifier with a deep understanding of the task.

#### IV. PROPOSED SYSTEM

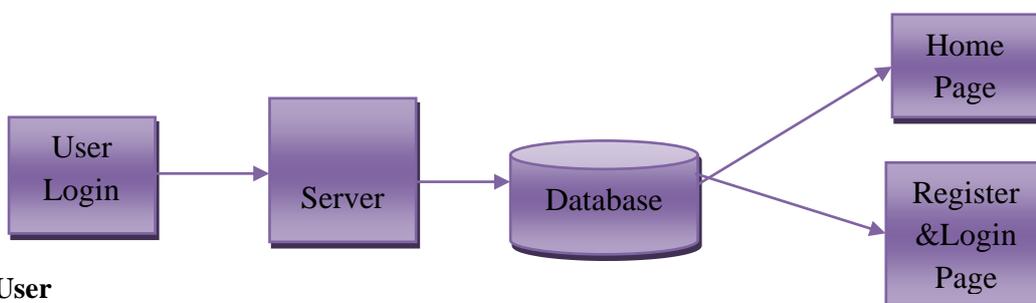
BERT (Bidirectional Encoder Representations from Transformers) is a Natural Language Processing Model proposed by researchers at Google Research in 2018. It is a pre-trained model that can be fine-tuned for various NLP tasks such as sentiment analysis, named entity recognition, and question answering. BERT uses a transformer architecture, which is an encoder-decoder network that uses self-attention on the encoder side and attention on the decoder side. The architecture of BERT consists of two models: BERT BASE and BERT LARGE. The BASE model has 12 layers in the Encoder stack, while the LARGE model has 24 layers in the Encoder stack. The BASE model contains 110M parameters, while the LARGE model has 340M parameters. BERT also uses many previous NLP algorithms and architectures such as semi-supervised training, OpenAI transformers, ELMo Embeddings, ULMFit, and Transformers.

- Scheme supports public verification and efficient user revocation.
- Each data block generates an authentication tag which is bound with the block.
- The security of our scheme is reduced to the assumptions of computational

The previous literature is mainly based on the use of the total evaluation score of products for product selection, and has obtained a wealth of research results. However, there are relatively few studies on the topic feature mining from the user review data of baby pacifier products provided by Amazon platform. This paper constructs LDA topic model, extracts topic features and measures topic intensity to understand the discussion bias of users. The research results of this paper provide theoretical support for improving the understanding of online shoppers purchase needs.

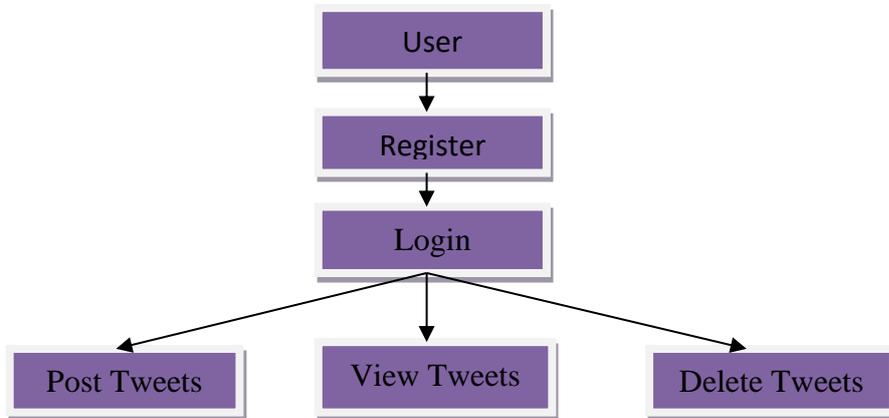
##### 1. User Interface Design

In this module we design the windows for the project. These windows are used for secure login for all users. To connect with server user must give their username and password then only they can able to connect the server. If the user already exists directly can login into the server else user must register their details such as username, password and Email id, into the server. Server will create the account for the entire user to maintain upload and download rate. Name will be set as user id. Logging in is usually used to enter a specific page.



##### 2. User

This is the first module of this project and he will be the administrator and has control over all the things. In this module User can login. After login user can view the products pictures. a user can be view products lists and user can be check the viewers and user can see the reviews of users and given the reviews.

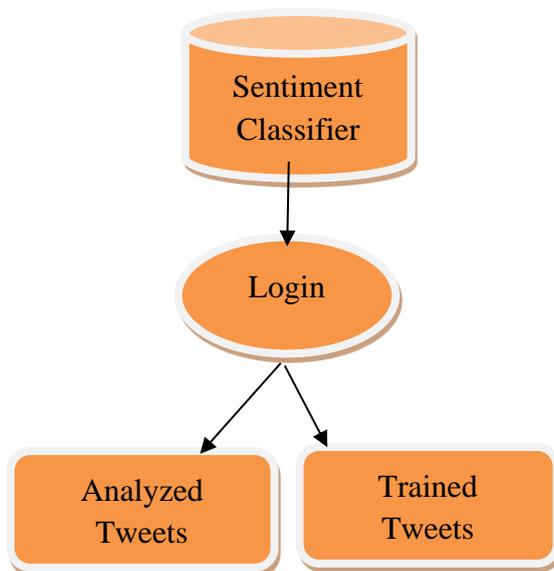


#### 4. Sentiment Classifier

This is the second module of this project. In this module admin should login. Admin will upload the products. Admin can add the reviews. Admin can have seen the viewers list and admin can check the user’s reviews.

#### LATENT DIRICHLET ALLOCATION (LDA)

We collected a large-scale dataset from the Steam platform, including four representative esports games: TEKKEN 7 (Fighting), Dota2 (MOBA), PUBG (BR), and CS:GO (FPS). All English reviews for these games uptoDecember2021onSteamwerecollected.Weiden tified the topics mentioned in the esports reviews using the Latent Dirichlet Allocation (LDA) algorithm. These keywords were then used to annotate 3,000 sentences in the dataset using three experienced annotators. The annotated dataset was used to fine-tune the training model on the input dataset with different downstream layers to achieve the best sentiment analysis perfor mance. Our hybrid model takes advantage of unsuper vised and supervised learning to improve the quality of sentiment analysis.



There were five stages to the framework. Using methods like language detection and filtering, noise reduction, spelling correction, and key information extraction (such as the user's SteamID, updated date, number of helpful and humorous votes, language tag and reviews), a fresh dataset of esports game reviews was gathered from Steam and preprocessed in the first phase. The preprocessed dataset was subjected to topic modelling using Latent Dirichlet Allocation (LDA) in the second step. This made it possible to automatically find themes and keywords related to every esports game. The highlighted subjects were utilised for annotation guidance and prevalence analysis in the next step. Three seasoned annotators were asked to classify certain parts of each review in the third phase using the themes and keywords determined in the first phase.

In the next stage, the sentiment analysis model was refined using the annotated dataset. In the fourth stage, the optimal way to do sentiment analysis tasks was to train a BERT-based model with a Transformer layer as the downstream layer. In order to determine how often each theme was in the four esports games, we examined their frequencies in the final stage. Furthermore, we used our trained BERT model to examine the sentiment polarity associated with each topic. Ultimately, we made judgements based on the findings for the whole dataset. The suggested framework includes aspect-based modelling, topic modelling, and data gathering and preprocessing.

## V. PROPOSED ALGORITHM

### BIDIRECTIONAL ENCODER REPRESENTATIONS FROM TRANSFORMERS (BERT)

BERT (Bidirectional Encoder Representations from Transformers) is a Natural Language Processing Model proposed by researchers at Google Research in 2018. It is a pre-trained model that can be fine-tuned for various NLP tasks such as sentiment analysis, named entity recognition, and question answering. BERT uses a transformer architecture, which is an encoder-decoder network that uses self-attention on the encoder side and attention on the decoder side. The architecture of BERT consists of two models: BERT BASE and BERT LARGE. The BASE model has 12 layers in the Encoder stack, while the LARGE model has 24 layers in the Encoder stack. The BASE model contains 110M parameters, while the LARGE model has 340M parameters. BERT also uses many previous NLP algorithms and architectures such as semi-supervised training, OpenAI transformers, ELMo Embeddings, ULMFit, and Transformers.

### 4.5 SYSTEM ARCHITECTURE

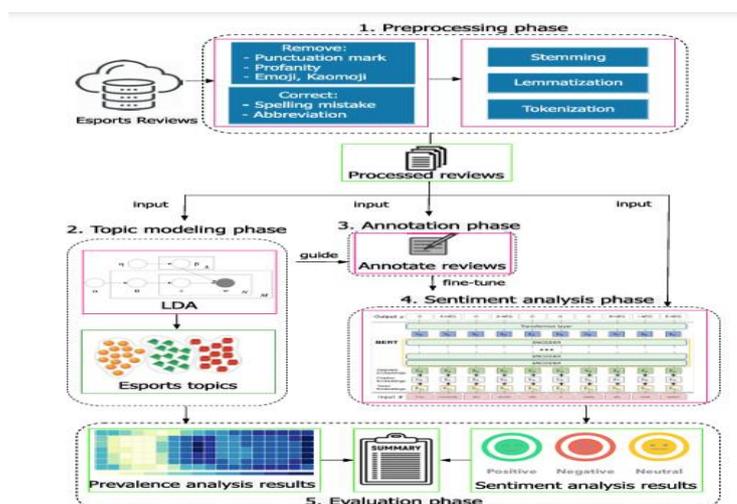


Figure 1. System architectures.

In this project data user can login a. Data user can also products pictures in the database? Data user can also a view product lists from the data. Data user cans also a product quality percentage. Data user can also view product reviews in the database. Data user can give the product reviews. Admin can login a data. Admin can also add a product. Admin can also have a view product list in the database. Admin can also a product quality percentage.

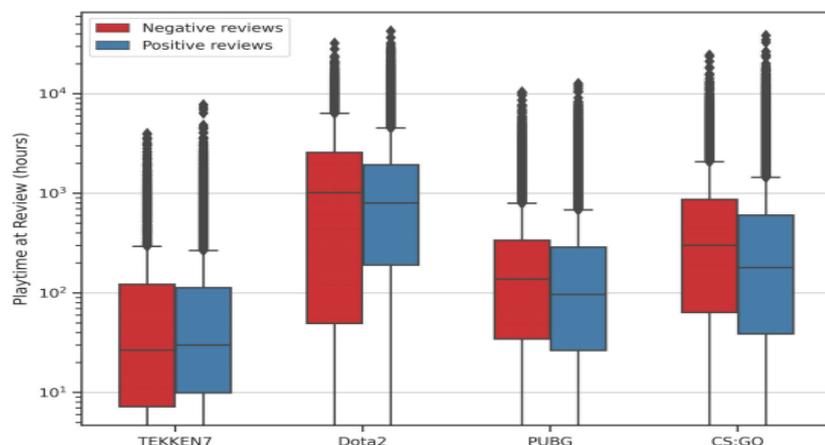


Figure 2. The positive/negative distribution of four esports reviews.

Games are long-term services whose quality is largely determined by how much time users spend with them. According to research by Lin et al. [7], game feedback is highly dependent on overall playtime, particularly in the esports sector where games are the primary emphasis. The distribution of favorable and unfavorable evaluations according to playtime is shown in Fig. 3. The horizontal axis displays the positive and negative distributions for each of the four games, while the vertical axis displays the amount of gameplay in hours. Early adopters of a game are often more likely to provide unfavorable reviews than good ones. But the more time they played, the less negative and better their assessments were. This makes sense since, while at first, players may not be acquainted with the visuals, tales, locations, and characters, as they gain experience, they tend to provide more favorable comments. Furthermore, game developers could include user input into their work, thus the longer a player plays a game, the more probable it is that the service will become better.

## VI. CONCLUSION

In esports, unbalanced gaming experience between professional players and noobs is a problem caused by the lack of methods for operators to quickly obtain useful information from noob players' feedback. To address this, we propose a hybrid approach of topic modeling and sentiment analysis to automatically analyze the vast number of game reviews from noob players. This will enable esports operators to better target their opinions and build a more balanced gaming environment. Our analysis of four representative esports games, TEKKEN7, Dota2, PUBG, and CS:GO, yielded several important insights. We extracted and summarized 16, 16, 15, and 16 topics for each game and divided them into GRT and PRT topics. We found that players value graphics, gameplay, and character in GRT, while their preferred PRT topics depend on the specific game, such as skill for TEKKEN7 and cheating for PUBG and CS:GO. We also employed a BERT-based model for sentiment analysis using the E2E-ABSA task on experimental datasets that reflected players' attitudes toward different topics. Our analysis indicated that negative attitudes toward PRT topics were generally higher than those toward GRT topics, suggesting that esports game operators should shift from being product providers to service providers.

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