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SENTIMENT ANALYSIS OF HOW DIFFERENTLY MALE AND FEMALE STREAMERS CHAT ON TWITCH.TV

ABSTRACT

Video gameplay has traditionally been social, with arcades providing an outlet for public play and consoles, allowing people to play together at home. Onlookers are not limited to being passive spectatorship as they are also provided the opportunity to engage directly with the player, with gameplay live streaming being the newest iteration. Live streaming of video games has become dominated in most countries by the website Twitch.tv, where the challenge concerns highly skilled players with minimal communication and exchange, conversely, prioritizes showmanship over gameplay. This paper focuses on common communication characteristics of viewers who often send single messages and streamers who elaborate. Based on a large real dataset of live stream chats, this paper uses sentiment analysis to explore and compare the findings of different communication theories regarding viewers and how they perceive streamers along the spectrum of different sentiments.

Keywords: video gameplay, sentiment analysis, live streaming, communication, twitch.tv

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INTRODUCTION

In today's area of the internet and online services, data is generated at incredible speed and amount. Businesses today are heavily dependent on data. Most of this data, however, is unstructured text coming from sources like emails, chats, social media, surveys, articles, and documents. The micro-blogging content coming from Twitter and Facebook poses serious challenges, not only because of the amount of data involved but also because of the kind of language used in them to express sentiments, i.e., short forms, memes, and emoticons.

Sifting through huge volumes of this text data is difficult as well as time-consuming. Also, it requires a great deal of expertise and resources to analyze all of that, which is not easily done. Corporations and businesses need to analyze textual data to understand customer activities, opinions, and feedback to successfully drive their business. All together, we can do the necessary analysis in the area of machine learning, and one of the analysis types that is considered is Sentiment Analysis, described in the following chapters.
Sentiment Analysis, or Opinion Mining, is a subfield of Natural Language Processing (NLP) that tries to identify and extract opinions within a given text. The aim of sentiment analysis is to gauge the attitude, sentiments, evaluations, attitudes, and emotions of a speaker/writer based on the computational treatment of subjectivity in a text.

Text Analytics has lots of applications in today's online world. By analyzing tweets on Twitter, we can find trending news and people's reaction to a particular event. Amazon can understand user feedback or reviews on specific products. BookMyShow can discover people's opinions about a movie. YouTube can also analyze and understand people's viewpoints on a video.

TextBlob and VADER are two powerful tools that will be used for analyzing sentiments from twitch comments. VADER defines itself as a parsimonious rule-based model for sentiment analysis of social media text and was created by C. J. Hutto and E. Gilbert. TextBlob is a Python library for processing textual data authored by Steven Loria.

The eSport suddenly became much like any other spectator sport and the media very quickly adjusted to that. Making use of the potential of commonly available broadband Internet connections and streaming technology, video game streaming websites were created, which allowed for the live broadcasting of video games on a global scale. Due to the fact that the streaming technology does not have high prerequisites of its own, it also allowed the regular, individual players to live broadcast their own gaming. This was facilitated by two major game streaming services that opened in the early 2010s: own3d.tv and Twitch.tv, the former of which has been closed in 2013.

Twitch.tv has developed over the years into an incredibly popular website and was bought by Amazon in September 2014 for $970 million (Wawro, 2014). Nowadays it is the most popular streaming service for Europe, both the Americas, and western Asia. It allows both normal players and eSport organizations to stream any game in any language (though English is strongly preferred by the majority). Since the site provides a subscription model (in which players are allowed to subscribe to a given person for $5/month for extra privileges), those particularly popular streamers use the website as their major source of income (Olejniczak, 2015).

The reasons for the growing popularity of video game streams are many. Firstly, due to the complexity of the games being streamed, people often watch the broadcasts to learn from the best and improve. The eSport tournament broadcasts on the other hand do not differ much from other regular sports broadcasts (in many European countries the major eSport events are nowadays available to watch on sports TV stations and in movie theaters). Those events take place live in regular sports venues and receive professional commentary and coverage in multiple languages.

All the above-described activities are facilitated by the website's chat feature. Every broadcast has its own chat room, a large section of the screen in which messages from other broadcast viewers can be viewed, and a text box through which one can enter and send their own messages. The individual streamers are usually very open to any queries and try to pass over their insights regarding the game; they also actively interact with their audience between the games via chat.

Those successful individual streamers have devoted fan communities that develop their own language varieties. The eSport game broadcasts also allow the spectators to actively participate in the chat. Due to the nature of the competitive events (normally 50 000 - 500 000 users watching live), the chat's nature differs significantly from the individual streams. Due to a relatively low message uptime and a huge number of participants, the chat is used mostly to express emotions as any kind of discussion is impaired by the constant influx of messages. However, this kind of situational context is truly unique: potentially hundreds of thousands of humans from different backgrounds engage in communication and attempt to simultaneously convey their attitudes and thoughts (Olejniczak, 2015)

METHODS

Natural language processing (NLP) is a subfield of linguistics, computer science, information engineering, and artificial intelligence concerned with the interactions between computers and human languages, and how to program computers to process and analyze large amounts of natural language data. Challenges in natural language processing frequently involve speech recognition, natural language understanding, and natural language generation. This paper is mostly focused on natural language understanding, a subtopic of NLP that deals with machine reading comprehension. This is considered to be an AI-hard problem, meaning they are the most difficult problems whose solutions require solving the central artificial intelligence problem: making computers as intelligent as people, commonly referred to as strong AI (Yampolskiy, 2013).

There is considerable commercial interest in the field of natural language understanding because of its application to automated reasoning, machine translation, question-answering, news-gathering, text categorization, voice activation, archiving, and large-scale content analysis, which is the main topic of this paper. The umbrella term natural language understanding can be applied to a diverse set of computer applications, ranging from small, relatively simple tasks such as short commands issued to robots, to highly complex endeavors such as the full comprehension of newspaper articles or poetry passages. Many real-world applications fall between the two extremes, for instance, text classification for the automatic analysis of emails and their routing to a suitable department in a corporation does not require an in-depth understanding of the text, but needs to deal with a much larger vocabulary and more diverse syntax than the management of simple queries to database tables with fixed schemata (Li, 2007).

This paper deals with a more complex form of natural language understanding which is not clearly defined even in human terms. Disagreements and arguments could easily occur during discussions between humans on whether a comment is positive, negative, or neutral in its sentiment expression. We could say that even human intelligence cannot fully agree on solving this problem and giving accurate results. We also know that artificial intelligence is not anywhere near-human levels of intelligence at the point of writing this paper, so expectations for a task as complex as sentiment analysis should be adjusted to reflect these facts.

TextBlob & NLTK

TextBlob is a Python library for processing textual data. It provides a simple API for diving into common natural language processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and more (Loria, 2020). TextBlob is built upon NLTK and provides an interface to perform a variety of NLP tasks described in the previous sentence (Malik, 2022).

NLTK is an acronym for *Natural Language Toolkit*, a platform for building Python programs to work with human language data. It provides interfaces to over 50 corpora and lexical resources

such as WordNet, along with a suite of text-processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning, wrappers for industrial-strength NLP libraries, and an active discussion forum.
Sentiment analysis using TextBlob is done using the sentiment property. TextBlob returns a named tuple of the form Sentiment (polarity, subjectivity). Polarity is afloat in the range [-1.0, 1.0], where -1 is the most negative and 1 is the most positive. Subjectivity is a number value from the range [0.0, 1.0] where 0.0 is very objective and 1.0 is very subjective (https://textblob.readthedocs.io/en/dev/quickstart.html#sentiment-analysis.).

VADER

VADER is a powerful open-source tool designed for analyzing the sentiment expressed in social media. VADER stands for *Valence Aware Dictionary and sEntiment Reasoner*. It is a simple lexicon and rule-based model for general sentiment analysis. The previous analysis was conducted to gauge the accuracy of VADER on a dataset consisting of tweets (140-character posts on Twitter). Using the parsimonious rule-based model to assess the sentiment of tweets, VADER was found to outperform individual human raters. Generalizations across contexts made by the tool were also more favorably performed than other relevant benchmarks (Hutto, 2014).

VADER was made using a combination of qualitative and quantitative methods to produce, and then empirically validate, a gold-standard sentiment lexicon that is especially attuned to microblog-like contexts. These lexical features were furthermore combined with consideration for five generalizable rules that embody grammatical and syntactical conventions that humans use when expressing or emphasizing sentiment intensity. It was found that incorporating these heuristics improved the accuracy of the sentiment analysis engine across several domain contexts (social media text, newspaper editorials, movie, and product reviews). Interestingly, the VADER lexicon performs exceptionally well in the social media domain. The correlation coefficient shows that VADER (r = 0.881) performs as well as individual human raters (r = 0.888) at matching ground truth (aggregated group mean from 20 human raters for sentiment intensity of each tweet). Surprisingly, when we further inspect the classification accuracy, we see that VADER (F1 = 0.96) actually even outperforms individual human raters (F1 = 0.84) at correctly classifying the sentiment of tweets into positive, neutral, or negative classes. In the end, VADER performed as well as (and in most cases, better than) eleven other highly regarded sentiment analysis tools. These results highlight the gains to be made in computer science when human is incorporated as a central part of the development process.

Because posts on microblogging sites like Twitter and comments on video streams on Twitch have many similarities, mostly pretending to be brevity and clear expression forced by the short format, we would expect VADER to perform admirably in sentiment analysis on such content, especially considering outstanding results explained in the previous passage.

Data collection

The data was collected from respective streams on Twitch.tv and pre-edited to allow their future examination with computer software. Twitch's API (Application Programming Interface) is a set of functions and procedures that allow other applications (such as our script) to access the features and data under Twitch's control. Our script makes an HTTP (HyperText Transfer Protocol) request to the API, which returns a response in the form of JSON (JavaScript Object Notation), which is an open standard file and data interchange format that uses human-readable text to store and transmit data objects consisting of attribute-value pairs and array data types.

Data were divided into two groups consisting of male and female streamers. For each gender, 5 well-known streamers were chosen, and comments were taken from their last 30 streams available as video on demand. The videos were thematically centered around gaming, specifically streamers screen casting their gameplay of popular titles like Fortnite, League of Legends, Hearthstone, and many others. Viewers were able to communicate in real-time with the streamers whose content they were enjoying by using the comments box next to the video. All selected streamers offer content in English so most of the comments were also in English.

RESULTS

From the dataset, the average number of comments is higher in the male part of the streamer population than in females (583,921 vs. 85,017), which suggests that male streamers have larger viewership. No significant conclusions could be made about the intensity of the interaction between the streamer and the audience. Therefore, considering the average number of comments per viewer, which is 11 for males, and 15 for females, we can better illustrate the relationship between the streamer and their viewers. The data shows that the average number of messages per user was higher on female streamer channels. The interaction between viewers and streamers was greater on female channels. The reason for this may be that female streamers pay more attention to viewers or viewers seek more attention from female streamers. Such theories could be examined by a deeper analysis of the context of the viewer's messages themselves.

The comment length of male streamer viewers is 4.5 and is only slightly shorter than the comment length of female streamers, 5.5. We can observe that Twitch comments are extremely short and concise. To put their length into context, a popular story format gained in popularity on the Internet in the past 10 years called Six Word Stories. The most famous example is: "For sale: baby shoes, never worn", often attributed to Ernest Hemingway, even though that link is considered unsubstantiated, and similar stories predate him. Even though the quantity of meaningful information spread across five words might seem questionable, examples such as Six Word Stories prove that significant amounts of information can be transferred in such a short format. One possible explanation for such brevity of messages is the limited time in which they are displayed on the screen. It does not make sense for commentators to engage in longer and deeper discussions.

The longest comment from each streamer gender has the same length of 500 words which can be recognized as the repetitive message of the bot, in other words, insignificant to our research. Before determining the frequency of word occurrence, the text needs to be slightly edited by removing stop words and performing stemming. Stemming is a process of linguistic normalization, which reduces words to their root and cuts off derivatives. For example, the word "connection" is reduced to its root: "connect". In the end, after punctuation marks are removed, the text is ready for word occurrence frequency analysis.

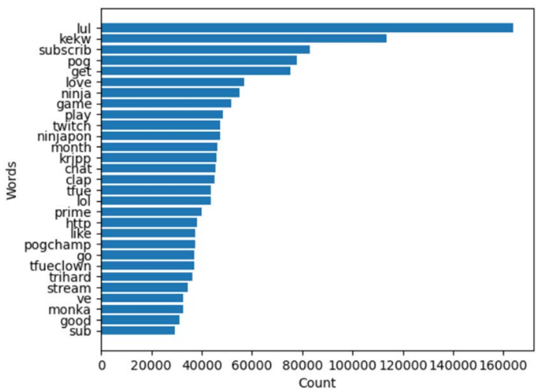


Figure 1. Word frequency distribution (male streamers)

From Figure 1, we can see that many of the most used words are abbreviations and acronyms. The word with the highest occurrence of over 160,000 times is *lul*, which is an emoji. The second-highest occurrence is *kekw*, also an emoji made from a viral meme. Subscribe is the root of the word subscribe and most probably comes from automatic notifications from the Twitch bot which is activated when a person subscribes to the streamer's channel. *Pog* refers to *PogChamp*, again an emoji described later. The words that follow are much more usual with textual communication: get, love, play, chat. Of course, many of them are thematically related to the gaming content that Twitch serves, for example, ninja, game, twitch. These kinds of words don't usually appear in datasets on which

VADER was trained, which makes us expect high numbers of neutrally rated comments.

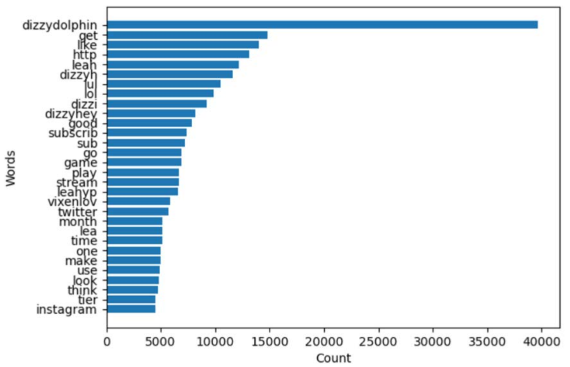


Figure 2. Word frequency distribution (female streamers)

Comments on female streamers' videos largely follow the same trends as those with male streamers. The highest occurring word, with almost 40,000 counted occurrences, is *dizzydolphin*, which is the name of a popular female Twitch gamer and streamer. The fourth highest occurring word is HTTP, which stands for *HyperText Transfer Protocol* and is the first part of hyperlinks that connect to other websites. The number of hyperlinks on female streamer videos hovers around 13,000, compared to just below 40,000 with male streamers. This is expected considering the fact that the average number of comments per male streamer is six times higher than that of female streamers. That is why it is helpful to look at the percentages of those hyperlinks in the total number of comments per gender. It figures out to 4% in female streamer cases, and 1.3% with male streamers.

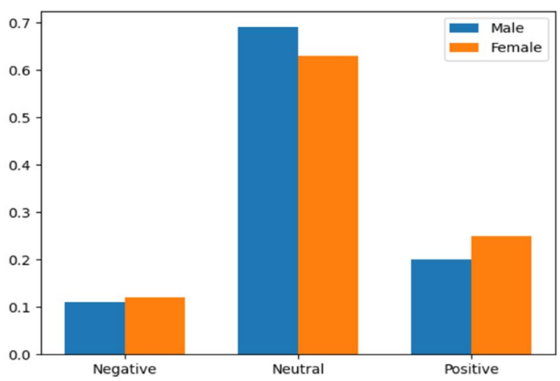
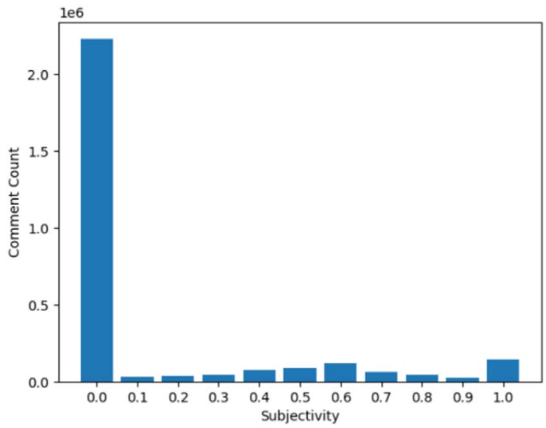


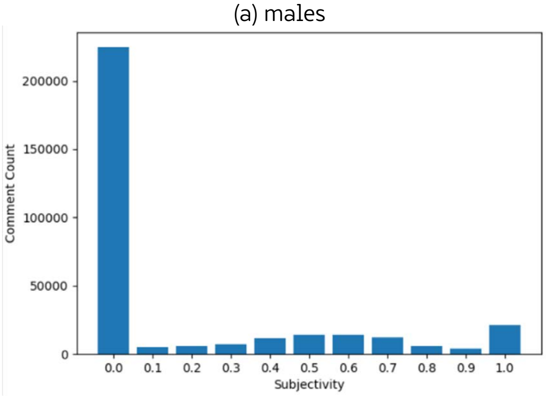
Figure 3. Female and male sentiment count

Sentiment analysis results show that female streamers have slightly more negative comments than their male counterparts but both sides have about 10%. Also, female streamers have more positive comments. The number of neutral comments is very high for both genders at around 60 – 70 %. The reason for that could be found in slang and another gaming-related language usage in comments, for which VADER cannot accurately identify the sentiment used. We can assume that VADER does not characterize those kinds of comments as strictly positive, because of the relatively low percentage of positive comments observed. This could, however, be a possible explanation for the relatively high percentage of neutral comments.

TextBlob can output two types of sentiment metrics: polarity (positive, neutral, or negative categories) and subjectivity (differentiation of facts and opinions). Facts are objective expressions about entities, events, and their properties. Opinions are usually subjective expressions that describe people's sentiments, appraisals, or feelings toward entities, events, and their properties. The concept of opinion is very broad. Much of the existing research on textual information processing has been focused on mining and retrieval of information, e.g., information retrieval, Web search, text classification, text clustering, and many other text mining and natural language processing tasks. Little work had been done on the processing of opinions until only recently. Yet, opinions are so important that whenever we need to make a decision, we want to hear others' opinions (Liu, 2010). TextBlob grades subjectivity as a floating decimal point number in the range [0.0, 1.0] where 0.0 is very objective and 1.0 is very subjective (https://medium.com/swlh/simple-sentiment-analysis-for-nlp-beginners-and-everyone-else-using-vader-and-textblob-728da3dbe33d). The results show a large bias towards objectivity. In fact, objectivity scores in the range between 0.0 and 0.1 completely dominate the whole subjectivity grade spectrum, with over 90% of comments being graded in that range. This appears to be counter-intuitive because we think of Twitch as a relaxing space where people come to unwind and find peace and joy in watching other people playing video games. It would appear logical that personal feelings and expressions dominate the objectivity required in life's other aspects that perhaps mentally drain us to the point where there is not nothing to do but watch Twitch streams. One possible explanation for this kind of unexpected result is that the models used to teach TextBlob did not include much of the slang specifically used in gamer or streamer culture. Therefore, it has trouble classifying those words on the subjectivity spectrum, and we can assume that the default set value is fully objective.



(a) males



(b) females

Figure 4. Subjectivity in comments of streamers

The occurrence of emojis is higher with female streamers, however, their overall occurrence is very low (Figure 4a) because the script converted some emojis to words whilst downloading the comments. From Figure 4b we can conclude that emoji converted to words occurs more often with male streamers. The overall occurrence of emoji converted to words is significantly higher than with usual emoji, which proves the argument expressed in the previous passage.

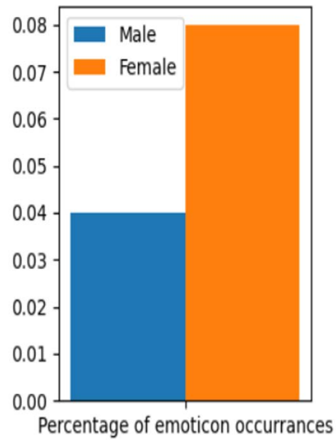


Figure 5. Female and male emoticon occurrence

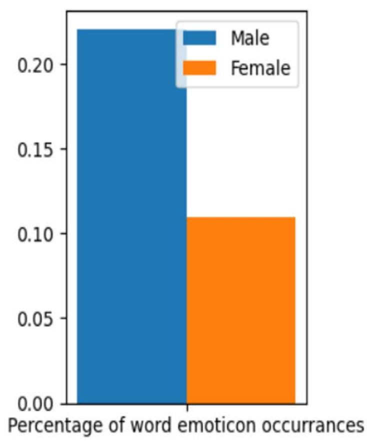
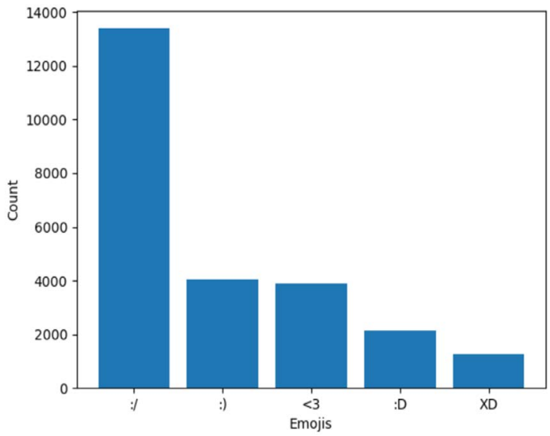
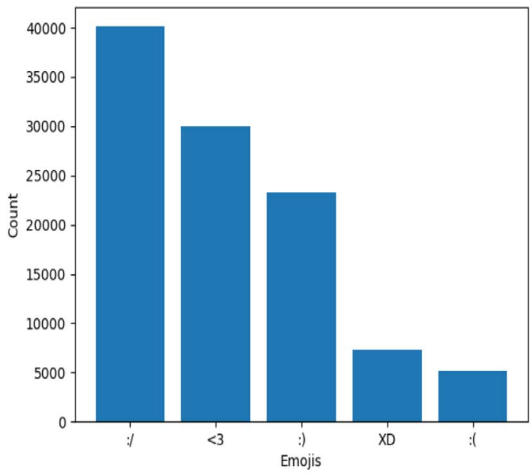


Figure 6. Female and male word emoticon occurrence

Figure 7 shows the 5 most used emojis in female streamers' comments. Emoji expressed in the comments of female streamers' videos ranged from neutral sadness to happiness and love. The highest emoji count amounts to somewhere around the interval of 12,000 to 14,000 and consists of just a colon and slash. These two simple symbols which usually represent interpunction here serve the purpose of expressing a complex emotion of a neutral feeling mixed with light sadness or disappointment. The emoji that follow the most occurred represent in total a happier sentiment, a smiley, heart, and wide-open smile emoji broadcast a lighter mood characterized as love towards self and others.



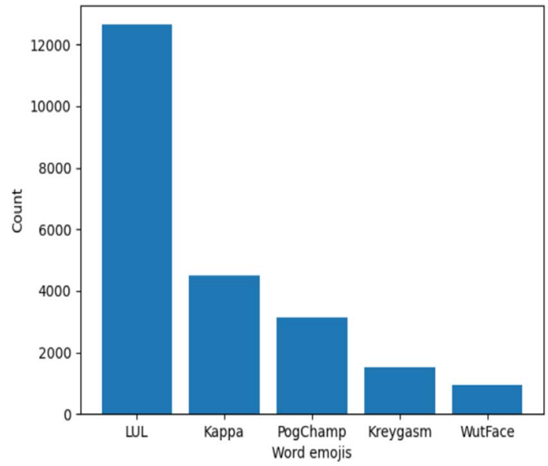
(a) females



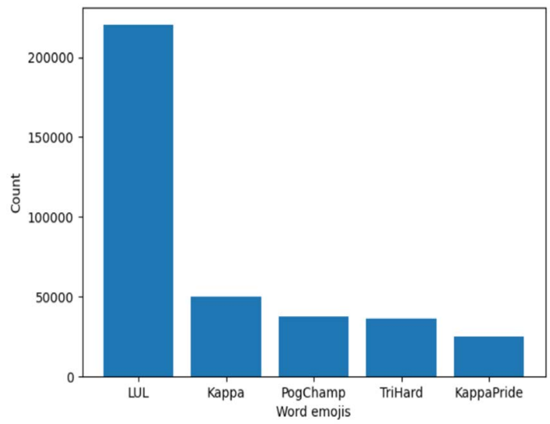
(b) males

Figure 7. Emoji distributions

Emoji recorded in a textual format, as described in a previous passage, expressed a feeling not describable with simple emotions like those emoji interpreted classically, again described in the previous passage. Such complex emotions are described in a table located below with possible conclusions of the sentiment expressed. Male streamers' textually interpreted emoji comments were largely like those expressed in their female companions' streams, at least while observing the three highest occurrences.



(a) females



(b) males

Figure 8. Emojis in textual format distributions

The following dashboard shows the legend for the above expressions.

Picture	Name	Meaning
	LUL	laughter
	Kappa	sarcasm
	PogChamp	amazement
	TriHard	excitement
	Kreygasm	satisfaction
	KappaPride	sarcasm
	WutFace	confusion and/ or disgust

Based on dataset analysis, the following hypotheses are proposed to statistically confirm if there are differences in the use of emojis for males and females during live online video streaming sessions.
H1: *The emoticon ":)" appears more frequently in the comments of female than male streamers.*
H2: *The emoticon ":/" appears more frequently in the comments of female than male streamers.*
H3: *The emoticon "<3" appears more frequently in the comments of female than male streamers.*
H4: *The emoticon "XD" appears more frequently in the comments of female than male streamers.*
H5: *The emoticon "Kappa" appears more frequently in the comments of female than male streamers.*
H6: *The emoticon "LUL" appears more frequently in the comments of female than male streamers.*
H7: *The emoticon "PogChamp" appears more frequently in the comments of female than male streamers.*

The two-proportions z-test is used to compare two observed proportions. It is performed by testing hypotheses. The null hypothesis (H_0) is defined as the case when two observed proportions are equal. The alternative hypothesis can be defined in multiple ways. The first is just to say that the proportions are not equal, which is called a two-tailed test because one proportion can either be larger or smaller than the other one. One-tailed tests define the alternative hypothesis as the case when one proportion is strictly larger or smaller than the other one. The test statistic is defined by the following formula:

$$z = \frac{p_A - p_B}{\sqrt{pq\left(\frac{1}{n_A} + \frac{1}{n_B}\right)}}$$

where p_A is the proportion observed in group A with size n_A, p_B is the proportion observed in group B with size n_B, and p and q are the overall proportions.

In our context, one population unit can be defined as every comment posted to Twitch. It would be very hard, although not impossible, to analyze every comment ever posted to that platform. In our context, when the p-value is lower than 5%, we can say that the proportions are in fact not equal. Because we are performing a one-tailed test, we can say exactly which proportion is larger than the other ones. For simplicity and better understanding, the test was set up in a way that tests if the proportion of comments on female streamers' videos is larger than that of male streamers' videos. So, if the p-value is close to 1, we can conclude that the proportion of comments on female streams is higher than that of male streams, and the opposite is true when the p-value approaches 0.

The results of testing the following hypotheses are summarized in Table 3. Overall, the results from testing the above hypotheses confirm certain differences between the comments of the male and female streamers. The conclusions from this research might help streamers in shaping their online communication strategies, as well as other experts such as market strategists, decision-makers, or other communication experts.

Table 1.

Hypothesis	p-value	z-value	Result
H1	> .05	694.35	Not supported
H2	> .05	13557.97	Not supported
H3	> .05	76.68	Not supported
H4	> .05	196.65	Not supported
H5	4.1e-7	206.44	supported
H6	1.1e-9	5892.12	supported
H7	1.04e-5	241.26	supported

DISCUSSION

Although the number of comments left on male streamers' videos was higher than those of their female counterparts, further examination explained that by the significantly larger viewership male streamers enjoy. When the results were pondered by taking into account the viewership numbers, the share of comments addressed to female streamers came up on top. Comment length is also statistically significantly higher with female streamers. Female streamers have more comments per viewer which means that the audience has a richer interaction with the streamer. The result of sentiment analysis showed that female streamers have more positive, but also negative interactions with their audience than male streamers. Most comments however were rated neutrally by VADER, which does not necessarily represent the true neutrality of the comments. The models used to train and create VADER probably were not exposed to gaming slang and other words used in gamer culture, so we can only assume the default subjectivity level that VADER outputs when it does not know the word is neutral, which is logical. Results could be improved with further research, as well as new training models using data with game-specific language. After analyzing the results, we concluded that male streamer viewers use more textual emojis compared to female viewers, who in most cases use emojis based on a pictured format. One possible conclusion one could draw with these premises is that male Twitch viewership is more tech-savvy and computer-orientated because emojis based on a pictured format is considerably more difficult to find and use for the average computer user. To sum that up, we can conclude that emojis based on text generally are the most frequently used emojis.

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ANALIZA SENTIMENTA I USPOREDBA MUŠKIH I ŽENSKIH RAZGOVARA NA *TWITCH.TV-U*

SAŽETAK

Videoigre tradicionalno su društvene igre, pri čemu arkade pružaju mogućnost javne igre, a konzole omogućavaju ljudima igrati zajedno kod kuće. S druge strane, promatrači igri nisu ograničeni na pasivno promatranje, nego imaju priliku izravno sudjelovati s igračem, pri čemu je *live streaming* igara najnovija inačica. *Live streaming* videoigara postao je dominantan u većini zemalja putem *web*-stranice *Twitch.tv*, gdje se izazov odnosi na iznimno vješte igrače s minimalnom komunikacijom i interakcijom, koji stavlja naglasak na zabavu umjesto na samu igru. Ovaj rad usredotočuje se na karakteristike komunikacije gledatelja koji često šalju pojedinačne poruke i *streamera* koji elaborira. Na temelju velikoga stvarnog skupa podataka o razgovorima uživo, ovaj rad koristi analizu sentimenta kako bi istražio i usporedio nalaze različitih teorija komunikacije u vezi s gledateljima i njihovim percepcijama *streamera* kroz spektar različitih osjećaja.

Ključne riječi: video igrica, analiza sentimenta, prijenos uživo, komunikacija, twitch.tv